UNITED STATES DISTRICT COURT
SOUTHERN DISTRICT OF NEW YORK

FEDERAL HOUSING FINANCE AGENCY, AS CONSERVATOR FOR THE FEDERAL NATIONAL MORTGAGE ASSOCIATION AND THE FEDERAL HOME LOAN MORTGAGE CORPORATION, Plaintiff, -against- NOMURA HOLDING AMERICA INC. et al., Defendants.	11 Civ. 6201 (DLC)

REVISED CORRECTED DIRECT TESTIMONY OF CHARLES D. COWAN

I, Charles D. Cowan, declare as follows:

1. I have over forty years of experience in statistical research and design. I received my Bachelor of Arts degree in Economics from the University of Michigan, my Master of Arts degree in Economics from the University of Michigan, and my doctorate in Mathematical Statistics from the George Washington University. I currently consult for numerous public and private sector entities on the design, implementation, and evaluation of research, and the synthesis of statistical and sampling techniques for measurement. My professional experience and academic tenures are included in my curriculum vitae, a true and correct copy of which is attached as **Plaintiff's Exhibit 1324**.

2. I have been retained by Quinn Emanuel Urquhart & Sullivan, LLP, counsel for Plaintiff Federal Housing Finance Agency ("FHFA"), (1) to develop a methodology to select a statistically valid random sample of loans from the Supporting Loan Groups (the "SLGs")

backing the Certificates purchased by the Federal National Mortgage Association ("Fannie Mae") and the Federal Home Loan Mortgage Corporation ("Freddie Mac," and, together with Fannie Mae, the "GSEs") for each of the seven securitizations of loans at issue in this litigation (the "Securitizations") and to extrapolate, to each SLG and in the aggregate, the re-underwriting results reported by FHFA's expert Robert W. Hunter and the appraisal results reported by FHFA's expert Dr. John A. Kilpatrick; and (2) to extrapolate certain results from RBS's diligence review.

3. FHFA has used the samples I have drawn to establish the falsity of Defendants' statements in the Prospectus Supplements regarding (i) the number/percentage of loans that were collateralized by properties that were owner-occupied; (ii) the number/percentage of loans that had LTV ratios above specified values; and (iii) whether the loans were originated in compliance with applicable underwriting guidelines of the originators. FHFA also has used my samples to enable it to estimate the percentage of loans in the population that contain misrepresentations as to one or more of these three attributes ("Defective Loans").

4. Based on my review of the loan tapes with respect to each of the Securitizations, I understand that there are approximately 15,806 loans in the SLGs.

5. For each sample, I initially selected 100 loans from the relevant SLGs for each Securitization. I chose this sample size because it is sufficient to allow, for each SLG, the determination of the proportion of defective loans along with a statement of the reliability of this proportion at a 95% confidence level with a maximum margin of error of +/- 10 percent. I stratified the population by credit score in selecting the sample, where possible, in order to potentially decrease the margin of error for my extrapolations and to improve the representativeness of the samples selected. I also supplemented these samples, where necessary,

to make it possible to still review 100 loans per SLG while accounting for missing loan origination files and loan files that could not be re-underwritten. In supplementing the samples, I used the same method by which I drew the initial samples.

6. When I received the reviews of the loans in the samples from Mr. Hunter and Dr. Kilpatrick, I extrapolated the results to the populations. Where the results were binary (*e.g.*, whether a loan did or did not comply with underwriting guidelines), I used a classical estimator based strictly on the counts of loans. For Dr. Kilpatrick's automated valuation model ("AVM") results, I used a Monte Carlo simulation to account for the variability associated with that model as well as sampling variability.

7. It is my opinion that my extrapolations of the results derived from the work of Mr. Hunter and Dr. Kilpatrick on the samples are reliable and can be used by the finder-of-fact to develop conclusions about the quality of the loans and quality of information used in the loan origination process.

8. In addition, after making some necessary assumptions given the incompleteness of the information, I performed extrapolations of results from RBS's diligence review.

I. Background on Sampling

A. Key Concepts In Statistical Sampling: Confidence Level, Margin of Error, And Stratification

9. Statistical sampling is often referred to as "probability sampling." The population refers to the group about which we wish to draw inferences, and the sample is a defined subset of that population. When a sample is randomly selected—that is, when each member of the population from which the sample is drawn has a known chance of being included in the sample—the sample provides an unbiased view of the population.

10. The precision—or reliability—of a sample is measured using the confidence level and the margin of error. As noted in the Federal Judicial Center's Reference Manual on Scientific Evidence, "In all forms of probability sampling, each element in the relevant population has a known, nonzero probability of being included in the sample. Probability sampling offers two important advantages over other types of sampling. First, the sample can provide an unbiased estimate of the responses of all persons in the population from which the sample was drawn; that is, the expected value of the sample estimate is the population value being estimated. Second, the researcher can calculate a confidence interval that describes explicitly how reliable the sample estimate of the population is likely to be."

11. The confidence level refers to the percentage of time that the actual value for the population will be within a specified range around the value for the sample. The margin of error refers to that specified range around the estimated value from the sample. For example, if the results of testing on the sample indicates that 50% of the mortgage loans were not originated in accordance with underwriting guidelines, then a confidence interval of 95% with a +/- 10% margin of error means that 95% of the time, the true percentage of loans not originated in accordance with underwriting guidelines in the population will be between 40% and 60%. This range is known as the confidence interval.

12. When a sample is used to test a binary question (for example, whether a loan was originated outside of the guidelines, or whether the owner occupancy status of the underlying property or the LTV of the loan was misrepresented), the margin of error depends on the sample value. The margin of error is greatest when the sample value is at 50% (*i.e.,* for 50% of the loans in the sample, there were false statements or omissions in the Prospectus Supplements concerning owner occupancy, LTV ratio, or adherence to underwriting guidelines). As the

sample value deviates from 50%, in either direction, the margin of error for that sample value decreases.

13. Although a sample drawn purely at random from a population is statistically valid, one can also draw a statistically valid sample using stratification. Stratification is a process where the population of loans is divided into mutually exclusive and exhaustive subgroups of loans. Stratification can only be carried out using variables known for the entire population prior to sampling. This is not the same as saying that every value is known for the entire population for a variable; here, missing values on a variable found on the loan tape may themselves be indicative of a defect, as these values should be available to the original underwriter.

14. Stratification commonly is used in sampling for two purposes. The first purpose is to increase the precision of the estimates from the sample. What we calculate from the sample is an estimate of the value in the population. The estimate has a margin of error due to sample-by-sample variability, which is directly related to the variability of the data being examined. When using a stratified sample, this variability is partitioned into two parts. The first part is the variability between the strata, and the second part is the variability within each of the strata. Variability between strata is eliminated by forcing the sample into these separate subgroups *a priori*, leaving only the second part of the variability. Stratification does not guarantee a diminution in the margin of error; it makes the diminution possible. Defendants' expert Dr. Barnett has not opposed stratification for this purpose.

15. A side benefit of stratifying to increase the precision of the estimates from the sample is that all other variables correlated with the variables used for stratification will also benefit in terms of improved representativeness. For example, when credit score is used for

stratification, the distribution of borrowers' debt-to-income ratios—which are correlated with the credit score—will likely be better represented by the sample.

16. The second purpose of stratification is inapplicable here. Stratification can ensure that some subgroups in the population are included in sufficient numbers so that it is possible to make separate estimates for each of the subgroups. This purpose of stratification does not apply here because the relevant inquiry instead is whether the Defendants made misrepresentations and omissions in the Prospectus Supplements for the Securitizations, not a subset of loans within those Securitizations.

B. Statistical Sampling Is Scientifically Valid

17. There is a wide body of peer-reviewed literature in the field of statistics that discusses the utility of statistical sampling for making reliable estimates of parameters in large populations of entities.

18. In addition, statistical sampling has been used successfully for hundreds of years as a research tool, and results from statistical sampling are replicable, meaning that statistical sampling meets the basic requirements as a scientific method.

19. There have been numerous applications of statistical sampling in academia, business, and government. For example, the nation's largest statistical agency, the United States Bureau of the Census, is authorized to base its surveys, including those on the extent of unemployment and the cost of living index, on samples.

20. Statistical sampling has also been widely employed in the American legal system. I have testified in over 50 cases, and sampling was accepted as scientifically valid in each of those cases in which a sample was used. Outside of my personal experience, courts routinely approve the use of sampling in cases in which claims as diverse as breach of contract, fraud, antitrust, trademark infringement, or tort are at issue.

21. The development of statistical sampling is grounded in mathematics and is not focused on the type of entity being sampled, but instead applies universally across any entity that can be counted. The accepted techniques of statistical sampling are the same regardless of the population being sampled, whether they are widgets, tires, people, or loan files. This principle results in a truism regarding the precision of the sample: The precision of the sample can always be quantified when the methodology is random sampling and the sample is random. Indeed, the result of random sampling should be expressed only as a value accompanied by a confidence interval. Thus, it is as accurate to sample produce for spoilage as to sample loans for non-compliance with guidelines, and the sampling range in each case will be quantifiable and reviewable in the same way.

C. Statistical Sampling Has Been Used To Value and Assess Portfolios of Loans

22. Statistical sampling has been and is used by the government and private businesses to value and assess pools of loans.

23. Federal regulators, who are charged with examining loans and other activities at the financial institutions they regulate, look at a sample of loans, as it would be impracticable to examine the overwhelming volume of loans held by such an institution. For example, the FDIC routinely relies on statistical samples to examine a bank's compliance with statutory and regulatory requirements. As the FDIC describes in a manual published on its website, bank regulators use statistical sampling of a bank's loan portfolio to determine, among other things: (i) the bank's adherence to its own lending policies, (ii) the adequacy of the quality of the bank's assets and collateral, (iii) whether the bank has charged the right interest rate and set aside the proper amount of reserves for the risk it faces. **Plaintiff's Exhibits 1520 and 1521.** Thus, the FDIC's objective of using sampling is to determine whether risks in a pool of assets have been properly presented and priced.

24. Similarly, based on my other engagements in this industry, I understand that private businesses that purchase and securitize mortgage loans routinely use statistical sampling to price loan portfolios. Loan originators, underwriters and investment banks, and servicers may use sampling for these and other purposes:

- Loan originators generally require the use of sampling for quality control purposes when purchasing loans from third parties, such as correspondent banks. Loan originators often require the seller to conduct a quality control review of a sample of loans to ensure compliance with guidelines as well as regulatory compliance.

- Underwriters and investment banks generally use sampling in fulfilling their due diligence obligations. More specifically, underwriters and investment banks rely on third-party due diligence firms to conduct credit and compliance reviews on random and adverse samples of loans selected from the pools of loans to be included in securitizations.

- Servicers generally use sampling to assess compliance with applicable servicing requirements.

- Experian, Transunion, and Equifax use sampling, specifically samples of loans taken from a small sample of banks, to create models to calculate credit scores.

- Financial institutions use sampling to conduct internal audit activities to ensure that transactions are correctly recorded as part of their quality control.

25. HUD has set forth quality control procedures and requirements for loan origination and servicing for FHA-insured loans. **Plaintiff's Exhibit 1522.**

II. Sample Design

A. Sample Selection Process

26. I was instructed that the relevant populations are the SLGs for each Securitization. I chose to draw an initial sample of 100 loans for the relevant SLGs for each Securitization. I primarily used the loan tapes produced by the Defendants in discovery to select the samples of loans. I understand that Defendants produced several loan tapes with information about the Mortgage Loans underlying each Securitization, but did not produce information identifying the loan tapes that were provided to the rating agencies. I performed equivalence testing between

the loan tapes produced by Defendants and the collateral tables in the Prospectus Supplements to determine which of the loan tapes produced by Defendants bore the closest statistical resemblance to the information contained in the Prospectus Supplements, and used these to draw the samples. In some cases, these loan tapes contained incomplete data as to which loans were in the SLGs, and in others, there was no loan tape available. Where this was the case, I used data from CoreLogic, a widely recognized provider of mortgage-related financial data.

27. After selecting these initial samples, I supplemented them for two reasons. *First*, in light of statements in the Court's order of December 3, 2012, concerning sampling (Dkt. 177), I retained the same sample design and expanded its focus, so that there were 100 loans per Supporting Loan Group (SLG) (rather than 100 loans per Securitization, as in my original design). *Second*, to account for missing loan origination files and loan files that could not be re-underwritten, I supplemented one sample, as I will explain in more detail. These supplementations occurred in several iterations. In neither case did I remove any loans from the samples.

28. In both cases, I supplemented the samples using the same methodology described in more detail below: the same FICO quartiles, the same random number generator, and the same loan tapes. The final, fully supplemented samples are set forth in **Plaintiff's Exhibit 1570**. The targeted sample size of 100 yields a 95% confidence level with a maximum margin of error of +/- 10% for binary questions.

29. The sample size necessary to achieve these target results for a binomial outcome is 95. I rounded up to 100 out of an abundance of caution. This "oversampling" created a cushion for my calculations and allowed for some flexibility should, for example, a loan in a

sample lack a loan file. Generally, it is not possible to know *a priori* what the margin of error will be for continuous variables, such as LTV, for reasons that I will explain.

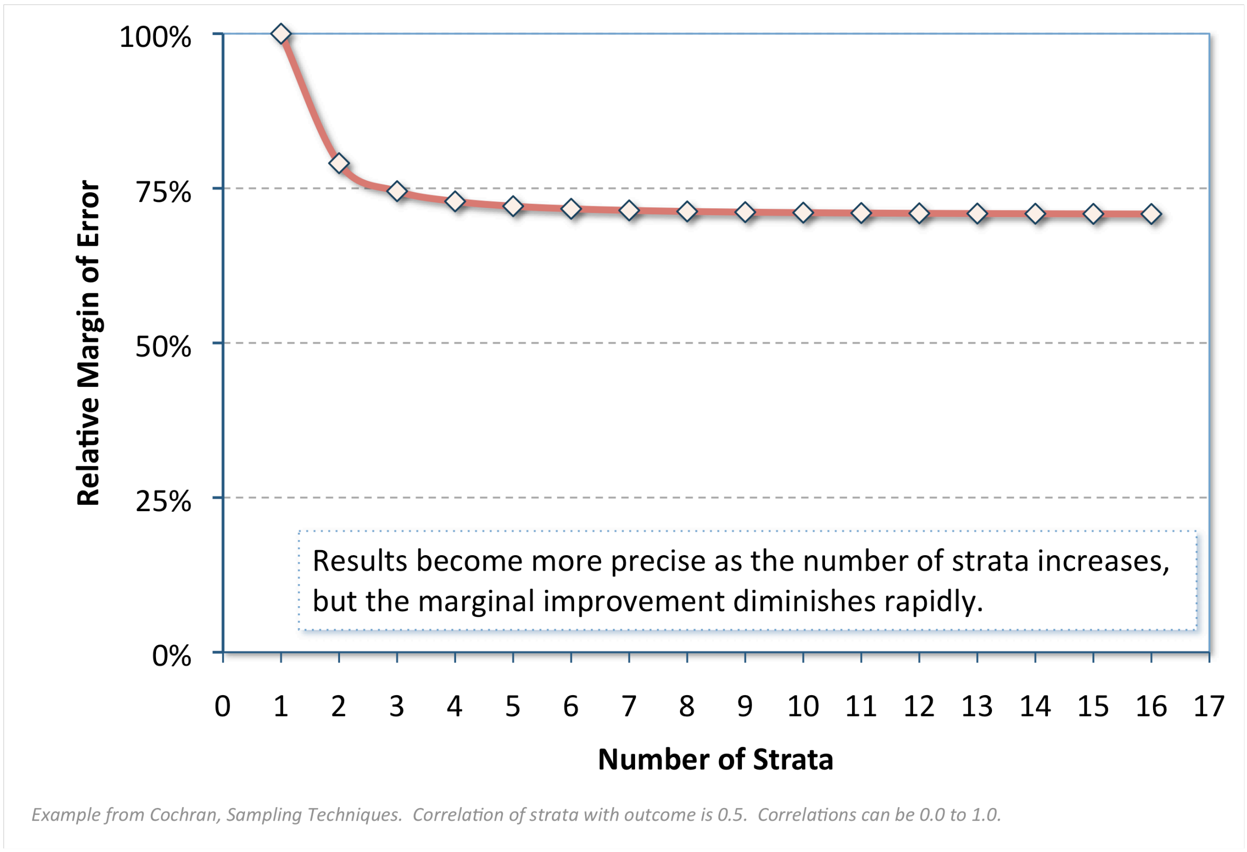
B. Stratification

30. The only variable I used to stratify the loan pools is the borrower's credit score, specifically the score as reported by the Fair Isaac Corporation Company (the "FICO score"), which generally appears for each loan on the loan tapes produced by the Defendants for the Securitizations. A borrower's FICO score can range from 350 to 850. A credit score is a number representing the creditworthiness of a person or the likelihood that person will pay his or her debts. It has been shown to be predictive of risk. In my experience, lenders, including mortgage loan originators, use credit scores to determine who qualifies for a loan, at what interest rate, and to what credit limits. In addition, in my experience, a borrower's credit score is highly unlikely to be misstated on a loan tape (unlike, for example, other loan tape data such as the loan-to-value, or LTV, ratio).

31. Although there are other factors available for stratification from the loan tapes, it is reasonable to limit the number of variables used to stratify the population. First, there are diminishing returns to reductions in the margin of error that result from adding more stratification variables. As the number of stratification variables increases, the margin of error tends to decrease, but at a slower and slower rate, until there are only very marginal reductions. Second, these decreases in the margin of error may not materialize if the stratifying variable is not correlated to outcomes of interest or if some of the subgroups created by the stratifying variables are empty (as I found to be the case when assessing the possibility of using the stratifying variable of loan originator and then sampling proportionally by vintage of the loan). Thus, there may be no benefit to stratifying by additional variables if the goal is simply to increase the number of strata without regard to the ultimate goal, which is reduction of the

margin of error. The chart below illustrates the diminishing returns associated with increasing the number of strata in an effort to increase precision.

Chart 1: Potential Reduction in Margin of Error and Diminishing Returns from Use of Additional Strata



32. Using FICO score as a stratifying variable, I divided the population of loans in each SLG into four equal-size groups with very low, somewhat low, somewhat high, and high credit scores defining the groups. Because I sampled each of the SLGs separately, the set of strata boundaries that define where one bucket ends and where the next begins (three strata boundaries define the four buckets in each SLG) will differ from SLG to SLG. This is not an issue for estimation from each sample, since the estimates are derived separately for each SLG, adding up across all the strata.

33. There are four strata created from credit score. Each stratum has the roughly same number of loans. A random number is generated for each loan in each stratum, in a manner that ensures that each loan has a nearly equal chance of being selected. After the random numbers are assigned, the loans are reordered (sorted) from lowest to highest random number. The first 25 loans in each stratum are selected to be in the sample, yielding 100 loans per SLG in each of the SLGs for the initial samples. When supplementing the samples, I used the same stratification process.

C. The Samples Are Random And Unbiased

34. The methodology that I have described for selecting a sample of loans from each SLG ensures that the sample is random and not subject to manipulation.

35. To demonstrate that the initial samples selected are representative of the population, I tested the sample against the population on eleven key variables (when available) from the loan tapes, including FICO score, debt-to-income ratio, LTV ratio, and occupancy type. For continuous variables (those where the values are numeric and increasing or decreasing in value, like FICO score and LTV ratio), I compared the mean of the sample distribution to the mean of the population distribution using a z-test, which is a common statistical method for determining that a sample value could have come from the population. For categorical variables (those where the values are categories, such as documentation type), I compared the distribution of the categories in the sample to the distribution of the categories in the population using a Chi-square test. Again, this is a common statistical method for determining that a sample distribution could have come from the population. At a 5% or less level of significance, I would expect 1 in 20 (5%) of the tests to fail by chance. The results of these tests are set forth in **Plaintiff's Exhibit 1569** and indicate a very high level of correspondence between the samples and their populations.

36. Dr. Barnett does not question the randomness of my initial samples. He does, however, purport to question the representativeness of my samples as analyzed by Mr. Hunter and Dr. Kilpatrick. His criticisms are narrow and incorrect.

III. Extrapolation

37. I used two different methods of extrapolation. For binary questions (such as whether a loan was materially defective), I used a classical estimator. For calculations concerning continuous variables (such as a recalculation of LTV), I employed a Monte Carlo simulation. I will describe in detail the methods of extrapolation I used, and the corresponding results, for each of the Re-Underwriting, Appraisal Accuracy, and Appraisal Standard estimates.

A. Re-Underwriting Estimates

1. Construction of the Dataset

38. Counsel provided me with a dataset of 723 loans with corresponding re-underwriting information. **Plaintiff's Exhibit 1570.** It is my understanding that the re-underwriting results are the subject of Mr. Hunter's testimony.

39. Although the original sample methodology indicated the selection of approximately 100 loans per SLG(s) for each Population, it is my understanding that a mortgage loan file was not always available (or contained incomplete information) for each sample mortgage loan selected. In the event of missing or incomplete loan files, I selected additional loans that served as a supplementation to the initial sample to achieve the re-underwriting of the number of loans per SLG necessary for my sample design, as described in paragraphs 27-28, above. For six of the seven SLGs, the number of loans Mr. Hunter was unable to re-underwrite totaled three or fewer loans each. I did not supplement these samples because I knew I would be able to achieve my targeted margin of error of +/- 10% at 95% confidence without doing so. (As I noted earlier, I drew more than the necessary 95 loans per SLG in anticipation of the

unavailability of some loans for underwriting.) I did supplement the sample for NAA 2005-AR6 Group 3 because there were 53 loans missing from the initial sample, adding a total of 96 loans to achieve a sample size of 131 re-underwritten loans for that SLG.

40. Dr. Barnett does not take issue with my decision not to supplement the six samples with three or fewer loans missing, nor does he take issue with whether those samples, as re-underwritten by Mr. Hunter, were representative of the SLGs. Instead, he takes issue only with the NAA 2005-AR6 Group 3 sample as re-underwritten, and asserts that I should have performed representativeness testing to demonstrate that the sample did not differ in material ways from the population. Dr. Barnett did not perform such representativeness testing himself, although he could have done so, and in fact did so in his report in the Goldman case. But Dr. Barnett fails to mention that I performed representativeness tests on not just the initial samples, but also on all supplemental samples, including that for NAA 2005-AR6 Group 3. Because the sample as re-underwritten is a combination of the initial and supplemental samples, I did not see a need to perform representativeness testing on the sample as re-underwritten, as I had already performed representativeness testing on both components. In addition, in supplementing the NAA 2005-AR6 Group 3 sample, I assumed that the loan files were missing or incomplete at random. This is an assumption that favors Defendants. The reason for this is that, in my experience, loan files are not missing at random. Instead, loan file are usually missing because there was a problem with the loan, such as that it was not originated in accordance with underwriting guidelines. Thus, assuming that loans with missing or incomplete loan files were no different from loans with loan files reduced the defect rates, to Defendants' benefit. Furthermore, a file that is missing today represents a problem for the investor as the file must be reconstructed if the borrower defaults (so that foreclosure procedures can commence) or if the

borrower pays off the loan in full (so that the borrower can receive title). Either situation will cost an investor in terms of time and money.

41. Moreover, any random sample is representative of the population because of the mathematics of randomization. Attempts to prove otherwise ignore the most basic underlying principles of probability theory. Attacking the utility of the sample through the failure of a single inconsequential representativeness test does not demonstrate that a sample is biased. The difference found using that test must correlate with what is being measured and be significant for the sample to be biased, as Dr. Barnett has conceded at his deposition. A pair of examples will demonstrate this. Suppose, as here, one is drawing a sample of mortgage loans to measure the rate at which the loans do not comply with a lender's underwriting guidelines. First, suppose that the differed from the population in the percentage of last names of borrowers whose last names start with the letter "C." No matter how large this difference, it is unlikely to impart bias, because the letter a borrower's last name starts with is unlikely to correlate with whether the loan is defective. Now suppose that a sample of mortgage loans differed from the population in average reported LTV, but the difference was less than 1%. The distribution of LTVs *might* correlate with what is being measured, *i.e.*, whether a loan is defective. But 1% is likely too small to introduce a significant bias.

42. Even if a difference were material and did correlate with the value being measured – not the case for any of the samples here – one must still determine the *direction* of the bias, as Dr. Barnett also admitted during his deposition. A sample could, for example, be biased *against* the finding of material defects in mortgage loans. I believe that, if there is any bias introduced by loans that cannot be re-underwritten, it is *against* the finding of material

defects. The reason is that, in my experience, as I have explained, when loans are missing loan files, they are missing because there were problems with how the loans were originated.

43. Finally, all that a demonstration of bias in a sample—again, not present here—would mean is that I would use a method of extrapolation other than the classical estimator. As Dr. Barnett admitted, the only bias that could conceivably be present here—although there is none—would be non-response bias, *i.e.*, a bias created by the fact that certain loans could not be re-underwritten. There are, as Dr. Barnett further admitted, established methods for correcting such bias; indeed, he is writing a book about them. At his deposition, Dr. Barnett could not suggest any such corrections I should have used but did not.

44. Dr. Barnett also was asked to calculate the margins of error at 95% confidence for each of the originators that originated more than 10% of the loans in a particular SLG. Dr. Barnett does not use any of the statistical techniques available to him to reduce the margin of error in his calculations, but I also do not understand his calculations to be relevant to any of the issues in this litigation. As I testified at my deposition, each loan was re-underwritten to the guidelines of the particular originator, and what is being measured is deviation from guidelines as a group. That is why I did not design my sample to achieve particular margins of error at the 95% confidence level for originators at the SLG level. Moreover, as I also explained at my deposition, Dr. Barnett's selection of originators who originated 10% or more of the loans in each SLG is arbitrary and convenient for the argument he wishes to make. If Dr. Barnett were correct that estimates for each originator were necessary, then he would have to provide an estimate for every originator in each SLG, which he does not do. If one were to attempt to do this using a sample, one would be forced to pull a substantial number of loans for every originator—even those who have just one or two loans per SLG. This would require a sample

size that was very close to the size of the entire population, because in many cases, one would have to take all loans for particular originators. Finally, as I explained at my deposition, if this exercise were in fact necessary, there are other techniques one could use—but which Dr. Barnett did not employ—to increase the precision of individual originator estimates, such as combining loans for each originator across SLGs, which would increase the precision of the estimate.

2. Extrapolation

45. I will now provide the extrapolation of Mr. Hunter's results on the aggregate level (one estimate for all seven SLGs) and on an individual level (one estimate for each SLG) and describe the methods used to extrapolate these results from the samples to the populations.

(a) Methodology

46. There are several statistically valid methods of extrapolating the results of the tests conducted on the sample to the populations. The actual method to be used depends on the availability of the data and the relationships between the variables in the sample. For extrapolating Mr. Hunter's re-underwriting results, I chose to use a classical estimator based strictly on the counts of loans.

47. Dr. Barnett does not take issue with my use of a classical estimator or claim there is a different method of extrapolation I should have used for these results. He asserts, however, that he does not know why I chose a classical estimator. I do not fully understand this criticism. A classical estimator is called "classical" for a reason, specifically, that it is the standard method of extrapolating the results of binary questions. In other words, one should not have to explain why one has used a classical estimator when extrapolating the results of a binary question, but instead why one has not. I also note that, in his own extrapolations of the results of Defendants' re-underwriting expert's results, Dr. Barnett used a classical estimator as well.

(b) Aggregate Level Results

48. Approximately 68.56% of the loans underlying the full set of SLGs were found to have underwriting defects that substantially increased the credit risk of the loans ("Materially Defective"). All estimates are provided with corresponding 95% confidence levels. The margin of error for the materially defective rate of 68.56% is 3.91%, which means there is a 95% probability that the population defect rate is between 64.65% and 72.47%, and there is only a 2.5% chance that the population defect rate is less than 64.65%. On a dollar-weighted basis, at least 70.09% of the loans were materially defective. This estimate has a margin of error of 4.47%. Thus, there is a 95% probability that the population dollar-weighted defect rate is between 65.62% and 74.56%, and there is only a 2.5% chance that the population dollar weighted defect rate is less than 65.62%. Note also that a higher dollar-weighted proportion, 70.09%, relative to a loan-weighted proportion, 68.56%, can result only if defects are more likely to occur in larger loans. This difference indicates a further bias in the underwriting process on the part of originators.

(c) SLG Level Results

49. The rate of materially defective loans for each SLG is computed as the number of loans determined to be materially defective divided by the total number of loans reviewed in the sample, computed within and using the four FICO strata. With the sample design employed for the selection of loans to be re-underwritten, the defect rate can be computed simply as the number of defective loans in the sample divided by the total number of loans in the sample. The results for the SLGs, as well as the 95% confidence intervals and margins of error, are presented in **Plaintiff's Exhibit 1523**, which I reproduce in Table 1 below.

Table 1: Materially Defective Rates for the SLGs (Count Estimate)

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	60.92%	53.71%	67.72%	7.01%
NHELI 2006-FM1 Group 1	70.00%	60.20%	78.59%	9.20%
NHELI 2006-FM2 Group 1	72.00%	62.24%	80.41%	9.09%
NHELI 2006-HE3 Group 1	66.63%	56.56%	75.68%	9.56%
NHELI 2007-1 Group 2-1	66.43%	57.26%	74.69%	8.72%
NHELI 2007-2 Group 1	69.54%	59.56%	78.33%	9.39%
NHELI 2007-3 Group 1	63.83%	53.69%	73.12%	9.71%
Aggregate	**68.56%**	**64.65%**	**72.47%**	**3.91%**

50. The materially defective rate presented in **Plaintiff's Exhibit 1523** is computed only on the 723 loans actually reviewed by Mr. Hunter. The estimates of materially defective rates in **Plaintiff's Exhibit 1523** are therefore, in my opinion, a conservative estimate of the actual rate of defective loans because, as I noted earlier, in my experience at the RTC and the FDIC, if a loan file is missing, there is typically a problem with the loan. Further, as I also noted earlier, if a loan file is missing there remains a problem in foreclosing on defaulted loans for which there is no file.

51. In the same way that materially defective rates can be computed as the ratio of materially defective loans divided by the total count of loans, a dollar-weighted materially defective rate can also be computed. This rate for each SLG is calculated as the ratio of dollars in the materially defective loans reviewed divided by the total dollars in the loans reviewed in the SLGs, again across the FICO strata used for sampling. **Plaintiff's Exhibit 1524**, which I have reproduced below in Table 2, shows the materially defective dollar-weighted rates and the corresponding 95% confidence intervals and margins of error for each SLG.

52. I computed the sampling variability of the defect rate using standard sampling theory equations. These equations are presented in **Plaintiff's Exhibit 1681**.

Table 2: Materially Defective Rate for the SLGs (Dollar Estimate Using Original Loan Balance)

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	62.62%	55.43%	69.35%	6.96%
NHELI 2006-FM1 Group 1	70.13%	60.31%	78.74%	9.21%
NHELI 2006-FM2 Group 1	70.36%	60.50%	78.99%	9.24%
NHELI 2006-HE3 Group 1	72.41%	62.61%	80.84%	9.11%
NHELI 2007-1 Group 2-1	67.99%	58.87%	76.11%	8.62%
NHELI 2007-2 Group 1	72.32%	62.51%	80.76%	9.13%
NHELI 2007-3 Group 1	63.61%	53.46%	72.93%	9.74%
Aggregate	**70.09%**	**65.62%**	**74.56%**	**4.47%**

53. The materially defective rates computed with counts or dollar weighting (original loan balance) for the SLGs are very similar. When the rates are weighted together using the population counts (**Plaintiff's Exhibit 1523**) or population dollars (**Plaintiff's Exhibit 1524**), the average materially defective rates continue to be similar (68.56% vs. 70.09%).

54. Dr. Barnett takes issue with how I calculate these dollar-weighted extrapolations. Dr. Barnett used a different method, known as bootstrapping, but he admitted that the differences between his calculations and the calculations in my back-up materials never exceed 1.5 percentage points. In addition, I provided two calculations, one using the exact binomial confidence intervals (which I reported in the body of my extrapolation report) and the other using the normal approximation (which I reported in my back-up materials). These two calculations also produce very similar results, with the largest difference just 1.7 percentage points. The exact binomial is what I believe to be the most accurate because it does not assume a normal distribution, as the normal approximation does. These small differences merely demonstrate that the approximations used—the normal, the binomial exact, or the bootstrap method—are the result of slightly different assumptions. These differences vanish as the sample size becomes larger and larger; the approximations are more and more reliable for larger sample

sizes. For small sample size the differences in the choice of an approximation differ are more likely to be noticeable, but, again, these differences are minimal.

55. I was also asked to extrapolate additional categories of re-underwriting conclusions and opinions from Mr. Hunter's re-underwriting work. For these categories, I extrapolated the underwriting defects that Mr. Hunter considered in his review potentially related to the increase of the credit risk of the loan. I employed the same extrapolation methodology described above for the count estimates at the 95% confidence level.

56. The first set of results includes loans that did not conform to the originator's underwriting guidelines. In general, I found a 65.42% materially defective rate for this category at a 95% confidence level with a margin of error of 3.99%, which means there is a 95% probability that the population defect rate for this category is between 61.43% and 69.41%. **Plaintiff's Exhibit 1525**, which I reproduced in Table 3 below, reflects the materially defective rate in each of the SLGs that were not underwritten in accordance with underwriting guidelines and did not have sufficient compensating factors to support an exception.

Table 3: Materially Defective Rate – Mortgage Loans That Did Not Conform to the Originators' Underwriting Guidelines (Count Estimate)

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	53.15%	45.93%	60.25%	7.16%
NHELI 2006-FM1 Group 1	69.00%	59.15%	77.70%	9.28%
NHELI 2006-FM2 Group 1	71.00%	61.18%	79.53%	9.18%
NHELI 2006-HE3 Group 1	61.63%	51.42%	71.14%	9.86%
NHELI 2007-1 Group 2-1	60.31%	51.02%	69.03%	9.00%
NHELI 2007-2 Group 1	64.42%	54.24%	73.71%	9.74%
NHELI 2007-3 Group 1	61.79%	51.61%	71.24%	9.82%
Aggregate	**65.42%**	**61.43%**	**69.41%**	**3.99%**

57. This second set of results pertains to instances where the collateral tables overstated the owner-occupancy status of the underlying mortgage loans. I found a 7.19%

materially defective rate for this category at a 95% confidence level with a margin of error of 2.34%, which means there is a 95% probability that the population defect rate for this category is between 4.85% and 9.52%. **Plaintiff's Exhibit 1526**, which I reproduced in Table 4 below, reflects the materially defective rate in each of the SLGs where owner occupancy was incorrectly reflected in the Prospectus Supplements' collateral tables.

Table 4: Materially Defective Rate – Collateral Tables Overstated the Owner Occupancy Status of the Underlying Mortgage Loans (Count Estimate)

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	11.09%	5.62%	19.83%	7.11%
NHELI 2006-FM1 Group 1	9.00%	4.07%	16.75%	6.34%
NHELI 2006-FM2 Group 1	8.55%	3.71%	16.25%	6.27%
NHELI 2006-HE3 Group 1	3.21%	0.58%	9.48%	4.45%
NHELI 2007-1 Group 2-1	4.18%	0.94%	13.01%	6.04%
NHELI 2007-2 Group 1	8.90%	4.01%	16.63%	6.31%
NHELI 2007-3 Group 1	6.65%	2.59%	13.71%	5.56%
Aggregate	**7.19%**	**4.85%**	**9.52%**	**2.34%**

58. The third category examines loans with LTV or CLTV ratios in excess of the guideline limits without required exception approvals. I found a 23.00% materially defective rate for this category at a 95% confidence level with a margin of error of 3.60%, which means there is a 95% probability that the population defect rate for this category is between 19.40% and 26.60%. **Plaintiff's Exhibit 1527**, which I reproduce in Table 5 below, reflects the materially defective rate in each of the SLGs that had a LTV and/or CLTV ratio in excess of the maximum set by the applicable guidelines, without exception approval.

Table 5: Materially Defective Rate – Mortgage Loans That Exceeded the LTV or CLTV Ratio Limits Set Forth in the Underwriting Guidelines Without the Required Exception Approvals (Count Estimate)

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	13.71%	9.31%	19.50%	5.09%
NHELI 2006-FM1 Group 1	21.99%	14.41%	31.27%	8.43%
NHELI 2006-FM2 Group 1	23.00%	15.21%	32.43%	8.61%
NHELI 2006-HE3 Group 1	24.17%	16.19%	33.74%	8.77%
NHELI 2007-1 Group 2-1	12.39%	7.20%	19.73%	6.26%
NHELI 2007-2 Group 1	25.54%	17.39%	35.20%	8.90%
NHELI 2007-3 Group 1	22.58%	14.85%	32.00%	8.57%
Aggregate	**23.00%**	**19.40%**	**26.60%**	**3.60%**

59. My extrapolations of Mr. Hunter's other findings are reflected in **Plaintiff's Exhibits 1528 - 1535** and are reproduced below.

Table 6: Materially Defective Rate – Mortgage Loans That Failed to Explain Recent Credit Inquiries, as Required by the Guidelines (Count Estimate) Plaintiff's Exhibit 1528

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	28.65%	22.54%	35.57%	6.52%
NHELI 2006-FM1 Group 1	52.00%	41.95%	61.92%	9.98%
NHELI 2006-FM2 Group 1	48.00%	38.00%	58.11%	10.06%
NHELI 2006-HE3 Group 1	44.42%	34.53%	54.64%	10.05%
NHELI 2007-1 Group 2-1	30.52%	22.54%	39.57%	8.52%
NHELI 2007-2 Group 1	46.87%	36.85%	57.08%	10.11%
NHELI 2007-3 Group 1	36.95%	27.58%	47.12%	9.77%
Aggregate	**45.28%**	**41.08%**	**49.49%**	**4.20%**

Table 7: Materially Defective Rate – Mortgage Loans That Were Missing Critical Credit Documents Required Under the Guidelines (Count Estimate) Plaintiff's Exhibit 1529

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	17.50%	12.55%	23.69%	5.57%
NHELI 2006-FM1 Group 1	32.00%	23.15%	41.92%	9.38%
NHELI 2006-FM2 Group 1	30.00%	21.35%	39.87%	9.26%
NHELI 2006-HE3 Group 1	24.21%	16.21%	33.78%	8.78%
NHELI 2007-1 Group 2-1	12.32%	7.16%	19.63%	6.24%
NHELI 2007-2 Group 1	28.62%	20.07%	38.49%	9.21%

NHELI 2007-3 Group 1	26.79%	18.46%	36.55%	9.04%
Aggregate	**27.52%**	**23.68%**	**31.36%**	**3.84%**

Table 8: Materially Defective Rates - Mortgage Loans That Exceeded DTI Ratio Limits Set Forth in the Guidelines without the Required Exception Approvals (Count Estimate)
Plaintiff's Exhibit 1530

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	10.80%	6.95%	16.17%	4.61%
NHELI 2006-FM1 Group 1	16.00%	9.56%	24.52%	7.48%
NHELI 2006-FM2 Group 1	17.00%	10.31%	25.71%	7.70%
NHELI 2006-HE3 Group 1	25.25%	17.11%	34.91%	8.90%
NHELI 2007-1 Group 2-1	18.31%	11.92%	26.48%	7.28%
NHELI 2007-2 Group 1	8.29%	3.73%	15.54%	5.91%
NHELI 2007-3 Group 1	19.54%	12.31%	28.67%	8.18%
Aggregate	**17.28%**	**14.04%**	**20.51%**	**3.24%**

Table 9: Materially Defective Rate – Reasonableness of Income That Was Not Assessed for Stated Income Loans, as Required by the Guidelines (Count Estimate)
Plaintiff's Exhibit 1531

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	22.90%	12.85%	36.66%	11.90%
NHELI 2006-FM1 Group 1	46.74%	26.92%	67.39%	20.24%
NHELI 2006-FM2 Group 1	33.96%	19.89%	50.51%	15.31%
NHELI 2006-HE3 Group 1	29.70%	11.35%	54.67%	21.66%
NHELI 2007-1 Group 2-1	31.16%	21.99%	41.73%	9.87%
NHELI 2007-2 Group 1	40.66%	23.36%	59.87%	18.25%
NHELI 2007-3 Group 1	7.12%	1.02%	22.61%	10.80%
Aggregate	**32.36%**	**24.91%**	**39.80%**	**7.44%**

Table 10: Materially Defective Rate – Failure to Identify and Investigate Unexplained Red Flags (Count Estimate) **Plaintiff's Exhibit 1532**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	10.55%	6.73%	15.91%	4.59%
NHELI 2006-FM1 Group 1	11.00%	5.73%	18.68%	6.48%
NHELI 2006-FM2 Group 1	13.00%	7.18%	21.11%	6.96%

NHELI 2006-HE3 Group 1	11.13%	5.76%	18.93%	6.58%
NHELI 2007-1 Group 2-1	12.27%	7.13%	19.56%	6.22%
NHELI 2007-2 Group 1	10.38%	5.18%	18.10%	6.46%
NHELI 2007-3 Group 1	13.33%	7.36%	21.63%	7.14%
Aggregate	**11.71%**	**8.99%**	**14.44%**	**2.72%**

Table 11: Materially Defective Rate – Information Contained on the Pre-Closing Tapes Did Not Match the Credit Characteristics of the Mortgage Loans (Count Estimate)
Plaintiff's Exhibit 1533

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	42.04%	35.10%	49.27%	7.08%
NHELI 2006-FM1 Group 1	47.00%	37.13%	57.07%	9.97%
NHELI 2006-FM2 Group 1	52.00%	41.88%	61.98%	10.05%
NHELI 2006-HE3 Group 1	47.30%	37.29%	57.47%	10.09%
NHELI 2007-1 Group 2-1	35.79%	27.36%	45.01%	8.82%
NHELI 2007-2 Group 1	47.04%	37.02%	57.25%	10.11%
NHELI 2007-3 Group 1	41.21%	31.52%	51.42%	9.95%
Aggregate	**47.15%**	**42.91%**	**51.40%**	**4.24%**

Table 12: Materially Defective Rate – Mortgage Loans That Were Not Properly Evaluated to Determine if They Were at Risk of Not Being Repaid or Not Adequately Supported by Collateral (Count Estimate) **Plaintiff's Exhibit 1534**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	60.92%	53.71%	67.72%	7.01%
NHELI 2006-FM1 Group 1	70.00%	60.20%	78.59%	9.20%
NHELI 2006-FM2 Group 1	72.00%	62.24%	80.41%	9.09%
NHELI 2006-HE3 Group 1	65.63%	55.53%	74.77%	9.62%
NHELI 2007-1 Group 2-1	65.38%	56.18%	73.74%	8.78%
NHELI 2007-2 Group 1	69.54%	59.56%	78.33%	9.39%
NHELI 2007-3 Group 1	63.83%	53.69%	73.12%	9.71%
Aggregate	**68.30%**	**64.39%**	**72.22%**	**3.91%**

Table 13: Materially Defective Rate – LTV/CLTV Values on the Pre-Closing Loan Tapes That Were Not Accurate (Count Estimate) **Plaintiff's Exhibit 1535**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	16.75%	11.90%	22.87%	5.48%
NHELI 2006-FM1 Group 1	22.99%	15.26%	32.35%	8.55%

NHELI 2006-FM2 Group 1	25.00%	16.92%	34.59%	8.83%
NHELI 2006-HE3 Group 1	24.13%	16.16%	33.69%	8.77%
NHELI 2007-1 Group 2-1	14.44%	8.81%	22.09%	6.64%
NHELI 2007-2 Group 1	24.50%	16.50%	34.08%	8.79%
NHELI 2007-3 Group 1	17.46%	10.61%	26.34%	7.87%
Aggregate	**22.96%**	**19.36%**	**26.56%**	**3.60%**

60. I was also asked to extrapolate for Mr. Hunter's total defect findings (*i.e.*, not limited to Loans with Substantially Increased Credit Risk) using the same methodology. Those extrapolations are reflected in **Plaintiff's Exhibits 1536 - 1547** and are reproduced below.

Table 14: Defective Rates for the SLGs (Count Estimates) Plaintiff's Exhibit 1536

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	85.07%	79.19%	89.62%	5.22%
NHELI 2006-FM1 Group 1	89.99%	82.51%	95.00%	6.24%
NHELI 2006-FM2 Group 1	95.00%	88.79%	98.31%	4.76%
NHELI 2006-HE3 Group 1	87.96%	79.89%	93.64%	6.88%
NHELI 2007-1 Group 2-1	78.65%	70.18%	85.51%	7.66%
NHELI 2007-2 Group 1	93.92%	87.12%	97.79%	5.34%
NHELI 2007-3 Group 1	88.58%	80.70%	94.02%	6.66%
Aggregate	**90.88%**	**88.56%**	**93.20%**	**2.32%**

Table 15: Defective Rates for the SLGs (Dollar Estimate Using Original Loan Balance) Plaintiff's Exhibit 1537

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	85.20%	79.29%	89.76%	5.24%
NHELI 2006-FM1 Group 1	89.94%	82.43%	94.97%	6.27%
NHELI 2006-FM2 Group 1	96.31%	90.48%	99.07%	4.29%
NHELI 2006-HE3 Group 1	88.00%	79.95%	93.66%	6.86%
NHELI 2007-1 Group 2-1	79.89%	71.56%	86.53%	7.49%
NHELI 2007-2 Group 1	94.52%	87.93%	98.13%	5.10%
NHELI 2007-3 Group 1	88.07%	80.09%	93.64%	6.77%
Aggregate	**91.29%**	**88.59%**	**94.00%**	**2.70%**

Table 16: Defective Rate Mortgage Loans That Did Not Conform to the Originators' Underwriting Guidelines (Count Estimate) **Plaintiff's Exhibit 1538**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	70.26%	63.28%	76.49%	6.60%
NHELI 2006-FM1 Group 1	88.99%	81.31%	94.27%	6.48%
NHELI 2006-FM2 Group 1	94.00%	87.48%	97.72%	5.12%
NHELI 2006-HE3 Group 1	77.88%	68.49%	85.55%	8.53%
NHELI 2007-1 Group 2-1	68.49%	59.39%	76.56%	8.59%
NHELI 2007-2 Group 1	82.75%	73.87%	89.59%	7.86%
NHELI 2007-3 Group 1	81.37%	72.40%	88.39%	7.99%
Aggregate	**84.51%**	**81.60%**	**87.42%**	**2.91%**

Table 17: Defective Rate – Mortgage Loans That Exceeded the LTV or CLTV Ratio Limits Set Forth in the Underwriting Guidelines Without the Required Exception Approvals (Count Estimate) **Plaintiff's Exhibit 1539**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	13.71%	9.31%	19.50%	5.09%
NHELI 2006-FM1 Group 1	21.99%	14.41%	31.27%	8.43%
NHELI 2006-FM2 Group 1	23.00%	15.21%	32.43%	8.61%
NHELI 2006-HE3 Group 1	24.17%	16.19%	33.74%	8.77%
NHELI 2007-1 Group 2-1	12.39%	7.20%	19.73%	6.26%
NHELI 2007-2 Group 1	25.54%	17.39%	35.20%	8.90%
NHELI 2007-3 Group 1	22.58%	14.85%	32.00%	8.57%
Aggregate	**23.00%**	**19.40%**	**26.60%**	**3.60%**

Table 18: Defective Rate –Mortgage Loans That Failed to Explain Recent Credit Inquiries, as Required by the Guidelines (Count Estimate) **Plaintiff's Exhibit 1540**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	42.76%	35.80%	49.99%	7.10%
NHELI 2006-FM1 Group 1	70.99%	61.25%	79.47%	9.11%
NHELI 2006-FM2 Group 1	66.00%	55.96%	75.07%	9.55%
NHELI 2006-HE3 Group 1	60.63%	50.41%	70.21%	9.90%
NHELI 2007-1 Group 2-1	38.70%	30.04%	47.98%	8.97%
NHELI 2007-2 Group 1	70.25%	60.31%	78.94%	9.32%
NHELI 2007-3 Group 1	57.57%	47.36%	67.32%	9.98%
Aggregate	**63.98%**	**59.98%**	**67.99%**	**4.00%**

Table 19: Defective Rate –Mortgage Loans That Were Missing Critical Credit Documents Required Under the Guidelines (Count Estimate) Plaintiff's Exhibit 1541

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	21.47%	16.05%	27.97%	5.96%
NHELI 2006-FM1 Group 1	33.00%	24.05%	42.95%	9.45%
NHELI 2006-FM2 Group 1	34.00%	24.93%	44.04%	9.55%
NHELI 2006-HE3 Group 1	25.25%	17.10%	34.90%	8.90%
NHELI 2007-1 Group 2-1	13.35%	7.96%	20.83%	6.44%
NHELI 2007-2 Group 1	28.62%	20.07%	38.49%	9.21%
NHELI 2007-3 Group 1	27.84%	19.43%	37.62%	9.10%
Aggregate	**29.15%**	**25.27%**	**33.04%**	**3.88%**

Table 20: Defective Rates - Mortgage Loans That Exceeded DTI Ratio Limits Set Forth in the Guidelines without the Required Exception Approvals (Count Estimate) Plaintiff's Exhibit 1542

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	10.80%	6.95%	16.17%	4.61%
NHELI 2006-FM1 Group 1	16.00%	9.56%	24.52%	7.48%
NHELI 2006-FM2 Group 1	17.00%	10.31%	25.71%	7.70%
NHELI 2006-HE3 Group 1	25.25%	17.11%	34.91%	8.90%
NHELI 2007-1 Group 2-1	18.31%	11.92%	26.48%	7.28%
NHELI 2007-2 Group 1	9.34%	4.44%	16.83%	6.19%
NHELI 2007-3 Group 1	19.54%	12.31%	28.67%	8.18%
Aggregate	**17.47%**	**14.22%**	**20.72%**	**3.25%**

Table 21: Defective Rate – Reasonableness of Income Where Not Assessed for Stated Income Loans, as Required by the Guidelines (Count Estimate) Plaintiff's Exhibit 1543

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	22.90%	12.85%	36.66%	11.90%
NHELI 2006-FM1 Group 1	46.74%	26.92%	67.39%	20.24%
NHELI 2006-FM2 Group 1	33.96%	19.89%	50.51%	15.31%
NHELI 2006-HE3 Group 1	29.70%	11.35%	54.67%	21.66%
NHELI 2007-1 Group 2-1	31.16%	21.99%	41.73%	9.87%
NHELI 2007-2 Group 1	40.66%	23.36%	59.87%	18.25%
NHELI 2007-3 Group 1	7.12%	1.02%	22.61%	10.80%
Aggregate	**32.36%**	**24.91%**	**39.80%**	**7.44%**

Table 22: Defective Rate – Failure to Identify and Investigate Unexplained Red Flags (Count Estimate) **Plaintiff's Exhibit 1544**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	11.96%	7.89%	17.50%	4.80%
NHELI 2006-FM1 Group 1	13.00%	7.22%	21.05%	6.91%
NHELI 2006-FM2 Group 1	13.00%	7.18%	21.11%	6.96%
NHELI 2006-HE3 Group 1	11.13%	5.76%	18.93%	6.58%
NHELI 2007-1 Group 2-1	12.27%	7.13%	19.56%	6.22%
NHELI 2007-2 Group 1	11.38%	5.91%	19.29%	6.69%
NHELI 2007-3 Group 1	13.33%	7.36%	21.63%	7.14%
Aggregate	**12.26%**	**9.49%**	**15.03%**	**2.77%**

Table 23: Defective Rate – Information Contained on the Pre-Closing Tapes Did Not Match the Credit Characteristics of the Mortgage Loans (Count Estimate) **Plaintiff's Exhibit 1545**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	44.26%	37.24%	51.50%	7.13%
NHELI 2006-FM1 Group 1	47.00%	37.13%	57.07%	9.97%
NHELI 2006-FM2 Group 1	53.00%	42.86%	62.94%	10.04%
NHELI 2006-HE3 Group 1	51.38%	41.24%	61.44%	10.10%
NHELI 2007-1 Group 2-1	38.78%	30.14%	48.05%	8.95%
NHELI 2007-2 Group 1	52.13%	41.94%	62.19%	10.12%
NHELI 2007-3 Group 1	47.37%	37.37%	57.53%	10.08%
Aggregate	**50.19%**	**45.92%**	**54.45%**	**4.26%**

Table 24: Defective Rate –Mortgage Loans That Were Not Properly Evaluated to Determine if They Were at Risk of Not Being Repaid or Not Adequately Supported by Collateral (Count Estimate) **Plaintiff's Exhibit 1546**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	82.85%	76.69%	87.76%	5.53%
NHELI 2006-FM1 Group 1	89.99%	82.51%	95.00%	6.24%
NHELI 2006-FM2 Group 1	95.00%	88.79%	98.31%	4.76%
NHELI 2006-HE3 Group 1	82.88%	74.03%	89.68%	7.83%
NHELI 2007-1 Group 2-1	75.60%	66.89%	82.88%	8.00%
NHELI 2007-2 Group 1	92.92%	85.86%	97.15%	5.64%

NHELI 2007-3 Group 1	87.58%	79.52%	93.27%	6.87%
Aggregate	**89.26%**	**86.76%**	**91.75%**	**2.49%**

Table 25: Defective Rate – LTV/CLTV Values on the Pre-Closing Loan Tapes That Were Not Accurate **Plaintiff's Exhibit 1547**

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	16.75%	11.90%	22.87%	5.48%
NHELI 2006-FM1 Group 1	22.99%	15.26%	32.35%	8.55%
NHELI 2006-FM2 Group 1	25.00%	16.92%	34.59%	8.83%
NHELI 2006-HE3 Group 1	25.13%	17.02%	34.76%	8.87%
NHELI 2007-1 Group 2-1	15.45%	9.62%	23.23%	6.81%
NHELI 2007-2 Group 1	24.50%	16.50%	34.08%	8.79%
NHELI 2007-3 Group 1	19.54%	12.30%	28.66%	8.18%
Aggregate	**23.47%**	**19.84%**	**27.10%**	**3.63%**

61. Finally, I was asked to extrapolate the results of Mr. Hunter's findings that did not employ AVM results. Those findings are in **Plaintiff's Exhibits 1548 - 1556** and are reproduced below.

Table 26: Materially Defective Rates for the SLGs (Count Estimate)

Plaintiff's Exhibit 1548

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	56.04%	48.81%	63.05%	7.12%
NHELI 2006-FM1 Group 1	65.00%	54.98%	74.13%	9.58%
NHELI 2006-FM2 Group 1	70.00%	60.13%	78.65%	9.26%
NHELI 2006-HE3 Group 1	64.63%	54.50%	73.86%	9.68%
NHELI 2007-1 Group 2-1	64.40%	55.17%	72.83%	8.83%
NHELI 2007-2 Group 1	59.38%	49.13%	69.06%	9.96%
NHELI 2007-3 Group 1	55.67%	45.47%	65.51%	10.02%
Aggregate	**63.72%**	**59.67%**	**67.76%**	**4.04%**

Table 27: Materially Defective Rate for the SLGs (Dollar Estimate Using Original Loan Balance) Plaintiff's Exhibit 1549

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	57.36%	50.13%	64.33%	7.10%
NHELI 2006-FM1 Group 1	64.63%	54.61%	73.79%	9.59%
NHELI 2006-FM2 Group 1	69.09%	59.15%	77.88%	9.36%
NHELI 2006-HE3 Group 1	70.88%	60.99%	79.49%	9.25%
NHELI 2007-1 Group 2-1	65.99%	56.81%	74.29%	8.74%
NHELI 2007-2 Group 1	64.32%	54.13%	73.63%	9.75%
NHELI 2007-3 Group 1	57.55%	47.34%	67.30%	9.98%
Aggregate	**66.11%**	**61.49%**	**70.72%**	**4.61%**

Table 28: Materially Defective Rate – Mortgage Loans That Did Not Conform to the Originators' Underwriting Guidelines (Count Estimate) Plaintiff's Exhibit 1550

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	48.27%	41.13%	55.47%	7.17%
NHELI 2006-FM1 Group 1	64.00%	53.96%	73.22%	9.63%
NHELI 2006-FM2 Group 1	69.00%	59.08%	77.76%	9.34%
NHELI 2006-HE3 Group 1	59.63%	49.40%	69.28%	9.94%
NHELI 2007-1 Group 2-1	57.23%	47.93%	66.13%	9.10%
NHELI 2007-2 Group 1	53.21%	43.00%	63.22%	10.11%
NHELI 2007-3 Group 1	53.63%	43.45%	63.59%	10.07%
Aggregate	**60.35%**	**56.26%**	**64.44%**	**4.09%**

Table 29: Materially Defective Rate – Mortgage Loans That Exceeded the LTV or CLTV Ratio Limits Set Forth in the Underwriting Guidelines Without the Required Exception Approvals (Count Estimate) Plaintiff's Exhibit 1551

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	3.15%	1.30%	6.92%	2.81%
NHELI 2006-FM1 Group 1	2.00%	0.18%	7.34%	3.58%
NHELI 2006-FM2 Group 1	2.00%	0.17%	7.38%	3.61%
NHELI 2006-HE3 Group 1	7.08%	2.95%	13.96%	5.50%
NHELI 2007-1 Group 2-1	5.18%	2.08%	10.94%	4.43%
NHELI 2007-2 Group 1	4.08%	1.17%	10.03%	4.43%
NHELI 2007-3 Group 1	6.16%	2.28%	12.97%	5.35%

Aggregate	**4.19%**	**2.52%**	**5.85%**	**1.66%**

Table 30: Materially Defective Rate – Mortgage Loans That Failed to Explain Recent Credit Inquiries, as Required by the Guidelines (Count Estimate) Plaintiff's Exhibit 1552

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	27.78%	21.72%	34.68%	6.48%
NHELI 2006-FM1 Group 1	47.00%	37.12%	57.07%	9.97%
NHELI 2006-FM2 Group 1	47.00%	37.03%	57.13%	10.05%
NHELI 2006-HE3 Group 1	43.42%	33.59%	53.64%	10.03%
NHELI 2007-1 Group 2-1	29.48%	21.61%	38.49%	8.44%
NHELI 2007-2 Group 1	40.83%	31.16%	51.08%	9.96%
NHELI 2007-3 Group 1	29.83%	21.14%	39.76%	9.31%
Aggregate	**41.95%**	**37.77%**	**46.13%**	**4.18%**

Table 31: Materially Defective Rate – Failure to Identify and Investigate Unexplained Red Flags (Count Estimate) Plaintiff's Exhibit 1553

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	10.55%	6.73%	15.91%	4.59%
NHELI 2006-FM1 Group 1	11.00%	5.73%	18.68%	6.48%
NHELI 2006-FM2 Group 1	13.00%	7.18%	21.11%	6.96%
NHELI 2006-HE3 Group 1	11.13%	5.76%	18.93%	6.58%
NHELI 2007-1 Group 2-1	12.27%	7.13%	19.56%	6.22%
NHELI 2007-2 Group 1	10.38%	5.18%	18.10%	6.46%
NHELI 2007-3 Group 1	12.33%	6.59%	20.47%	6.94%
Aggregate	**11.59%**	**8.88%**	**14.31%**	**2.71%**

Table 32: Materially Defective Rate – Information Contained on the Pre-Closing Tapes Did Not Match the Credit Characteristics of the Mortgage Loans (Count Estimate) Plaintiff's Exhibit 1554

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	34.56%	28.01%	41.69%	6.84%
NHELI 2006-FM1 Group 1	30.01%	21.42%	39.81%	9.20%
NHELI 2006-FM2 Group 1	42.00%	32.29%	52.18%	9.95%
NHELI 2006-HE3 Group 1	38.25%	28.76%	48.45%	9.85%
NHELI 2007-1 Group 2-1	31.67%	23.61%	40.76%	8.57%
NHELI 2007-2 Group 1	30.71%	21.92%	40.70%	9.39%

NHELI 2007-3 Group 1	28.92%	20.37%	38.77%	9.20%
Aggregate	**35.01%**	**30.93%**	**39.08%**	**4.08%**

Table 33: Materially Defective Rate – Mortgage Loans That Were Not Properly Evaluated to Determine if They Were at Risk of Not Being Repaid or Not Adequately Supported by Collateral (Count Estimate) Plaintiff's Exhibit 1555

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	56.04%	48.81%	63.05%	7.12%
NHELI 2006-FM1 Group 1	65.00%	54.98%	74.13%	9.58%
NHELI 2006-FM2 Group 1	70.00%	60.13%	78.65%	9.26%
NHELI 2006-HE3 Group 1	63.63%	53.47%	72.95%	9.74%
NHELI 2007-1 Group 2-1	63.35%	54.10%	71.86%	8.88%
NHELI 2007-2 Group 1	59.38%	49.13%	69.06%	9.96%
NHELI 2007-3 Group 1	55.67%	45.47%	65.51%	10.02%
Aggregate	**63.46%**	**59.41%**	**67.50%**	**4.04%**

Table 34: Materially Defective Rate – LTV/CLTV Values on the Pre-Closing Loan Tapes That Were Not Accurate (Count Estimate) Plaintiff's Exhibit 1556

Securitization (SLG)	Breach Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	5.48%	2.85%	9.88%	3.51%
NHELI 2006-FM1 Group 1	2.00%	0.18%	7.34%	3.58%
NHELI 2006-FM2 Group 1	3.00%	0.54%	8.77%	4.12%
NHELI 2006-HE3 Group 1	4.00%	1.02%	10.14%	4.56%
NHELI 2007-1 Group 2-1	6.18%	2.72%	12.22%	4.75%
NHELI 2007-2 Group 1	1.04%	0.04%	5.54%	2.75%
NHELI 2007-3 Group 1	1.04%	0.05%	5.52%	2.73%
Aggregate	**2.61%**	**1.27%**	**3.96%**	**1.35%**

B. Appraisal Accuracy Estimates

1. Construction of Dataset

62. Counsel provided me with a dataset of the 796 loans constituting the samples I drew with corresponding Loan Tape information. It is my understanding that Dr. Kilpatrick was not able to obtain reliable Automated Valuation Model ("AVM") estimates for 124 of the 796 loans. I identified the remaining 672 loans with an AVM result ("AVM Data") and based my

analysis on the information provided for this set of loans. The number of loans per SLG with an AVM result are identified in **Plaintiffs Exhibit 1557**, reproduced below. These data show the degree of inflation as judged by the percentage overstatement of the AVM result by the appraisal.

Table 35: Number of Loans with AVM Estimates (Count Estimate)

Securitization (SLG)	Original Sample Size	AVM Estimate Available
NAA 2005-AR6 Group 3	196	129
NHELI 2006-FM1 Group 1	100	94
NHELI 2006-FM2 Group 1	100	95
NHELI 2006-HE3 Group 1	100	88
NHELI 2007-1 Group 2-1	100	92
NHELI 2007-2 Group 1	100	88
NHELI 2007-3 Group 1	100	86
Aggregate	**796**	**672**

63. As with the samples as re-underwritten, Dr. Barnett takes issue with the samples for which the AVM produced results (the "AVM Samples"). He faults me for not having run representativeness tests, but he did not run them himself, although he did so in the Goldman case. As I describe above, it is standard to assume that differences do not introduce bias. Because Dr. Barnett did not measure the amount or direction of any bias, as he admitted during his deposition, he cannot say that the AVM Samples are biased.

64. Dr. Barnett also ignores important findings. Specifically, I provide in **Plaintiff's Exhibit 1561**, which I reproduce as Table 39 later in my testimony, a table setting forth the loan tape LTV ratios and the AVM sample loan tape LTV ratios. This table acts as a representativeness test for the loan tape LTV ratios. The values for these two columns are very similar, indicating a high degree of similarity. If one were to take the weighted average of the

LTV ratios, the distributions would not demonstrate a material difference. In other words, the sample would pass any representativeness test for loan tape LTV ratios. Because this is all that Dr. Kilpatrick measures, and all that I extrapolate, passing this test is sufficient to show that the samples can be properly extrapolated and that one can be secure in relying on the outcomes of the extrapolation. This is further confirmed by **Plaintiff's Exhibit 1558**, reproduced below, which shows that the weighted average LTV in the sample is close to that in the population.

Table 36: Results of the Test of Equality (Chi-Square Values)

Securitization (SLG)	Population Loan Tape LTV Equals Sample Loan Tape LTV	Population LTV Equals Simulation LTV
NAA 2005-AR6 Group 3	1.5	6190.4
NHELI 2006-FM1 Group 1	4.0	610.0
NHELI 2006-FM2 Group 1	1.1	868.2
NHELI 2006-HE3 Group 1	4.5	909.2
NHELI 2007-1 Group 2-1	7.6	1284.2
NHELI 2007-2 Group 1	7.7	1629.0
NHELI 2007-3 Group 1	2.1	1475.4
Aggregate	**26.8**	**35043.2**

2. Extrapolation

65. I will now describe the method I used to extrapolate these results from the samples to the populations.

66. In order to design an appropriate extrapolation method for these results, I had to take into account both sources of variability in the AVM Data: (i) the variability due to the use of a sample of loans from the population of loans in each deal ("Sampling Variability"), and (ii) the variability in Dr. Kilpatrick's AVM estimates ("AVM Variability"). Sampling Variability is present whenever one uses a sample rather than an entire population. It occurs because there can be (and are expected to be) some differences between two samples of equal size drawn from the

same population. By looking at a sample, an estimate of the true population value (in this case, the difference between the AVM and the appraisal) can be made, but with some uncertainty because of the review of only a subset of loans. As I explained in paragraphs 10-11 above, this uncertainty is traditionally expressed as a margin of error at a given confidence level, or as a confidence interval.

67. The AVM Variability (also known as model variability) is derived from the lower and upper confidence bounds reported for each loan in the AVM Data. The variables that identified the lower and upper confidence intervals are "Lower 95% Confidence Interval" and "Upper 95% Confidence Interval."

68. Were we to examine *all* the loans in a population, there would be no sampling variability, only the model variability from the AVM. Alternatively, if we were to look at a sample of loans and find that the AVM and the appraisal were exactly the same for each loan in the sample, there would be no model variability but there would be some uncertainty due to sampling. In our analysis, there is uncertainty that results both from the modeling effort (the AVM) and from the review of only a sample of loans.

69. Because of the presence of both Sampling and AVM Variability, the weighted average extrapolation method I employed with respect to Mr. Hunter's re-underwriting work could not be used, as it accounts only for Sampling Variability. Instead, I used a Monte Carlo simulation to take both Sampling Variability and AVM Variability into account.

70. A Monte Carlo simulation runs a model a very large number of times with random inputs to the variables in the model to calculate probabilities for outcomes (see Robert and Casella, 2004). A simple illustration of a Monte Carlo simulation is flipping a single coin many times. The distribution of the outcomes of heads and tails will provide the probability for

that coin that it will come up heads or tails on any given flip. If the coin is not a fair coin (*i.e.,* not a 50% chance of heads and 50% chance of tails) the Monte Carlo simulation will still give the correct probability of that coin coming up heads or tails. A slightly more complicated model has the coin used for the test being selected at random before the coin flip. If there is a large pool of "unfair" coins (*i.e.,* with different chances of coming up heads or tails), then the Monte Carlo simulation estimates the likelihood that the average of all coins will come up heads a certain proportion of the time, and the variability of this outcome. Note now that there are two sources of variability: the variability of the fairness of the coin that is selected (how close or far from 50/50) plus the variability of the outcome (heads or tails). In many respects, this illustration is akin to the situation we face with a sample of loans and an AVM performed on the sample.

71. Monte Carlo simulations have been used in statistics since the 1940s. The method is especially useful for obtaining numerical solutions to problems too complicated to solve analytically. A wide body of peer-reviewed literature in the field of statistics discusses the utility of Monte Carlo simulations. Dr. Barnett has himself used Monte Carlo simulations in his work. In fact, the bootstrap method he used to evaluate the variability of the dollar-weighted defect rate is another form of a Monte Carlo simulation, in many ways identical to the methods I use for the AVM extrapolation. He also acknowledges that they are the best method for solving complex equations with multiple variables, as we have here.

72. I used a Monte Carlo simulation here because it allows me to account simultaneously for both Sample and AVM Variability. It does so by creating new samples ("New Samples") from the AVM Data and by regenerating an AVM estimate on the loans in the New Sample, as I will explain.

73. The Monte Carlo simulation I used has two steps. First, I randomly selected loans, on a per SLG basis, from the AVM Data to repeatedly re-create the initial AVM sample (the New Sample) for that particular SLG. The selection of loans in the New Sample is done with replacement, meaning that a loan can be selected in the New Sample multiple times. Replacement allows the creation of New Samples that differ from the original sample with the same number of loans as the original sample. Since the original sample was random, the New Samples should emulate the distribution of potential outcomes available from the sampling process.

74. Second, for each loan selected in the New Sample in step 1, I randomly re-generated an AVM estimate, assuming a normal distribution with a mean of the Kilpatrick AVM estimate and the standard deviation calculated from the confidence intervals reported in the AVM Data. This process is akin to re-running the AVM a large number of times, because it provides a distribution of values from the AVM estimate, thus allowing me to account for AVM Variability.

75. I repeated the simulation 1,000 times for each individual SLG, generating a New Sample with each iteration. Once the 1,000 iterations were complete, I took the average AVM for each loan in each SLG's recalculated AVM estimate, along with the standard deviation of the simulated values in order to encapsulate 95% of the simulated values. This distribution allowed me to calculate the probabilities for each SLG.

3. Average Simulation Estimates

76. Based on the average simulation results, I was able to conclude that the Original Appraisal value reported in the Loan Tapes was higher for 64.7% of the population and the overall average inflation rate is 11.1%, with a lower bound of 8.5% and an upper bound of 13.7% at the 95% confidence level. **Plaintiff's Exhibit 1559**, which I reproduce in Table 37,

shows the average inflation rate for each SLG based on the average simulated value of the 672 loans, with the upper and lower bounds at the 95% confidence level.

Table 37: Average AVM Inflation Rate (Count Estimate)

Securitization (SLG)	Average AVM Inflation Rate	95% Lower Bound AVM Inflation Rate	95% Upper Bound AVM Inflation Rate
NAA 2005-AR6 Group 3	6.0%	2.0%	10.0%
NHELI 2006-FM1 Group 1	6.6%	1.6%	11.7%
NHELI 2006-FM2 Group 1	14.9%	8.4%	21.3%
NHELI 2006-HE3 Group 1	12.0%	6.1%	17.8%
NHELI 2007-1 Group 2-1	5.1%	0.7%	9.4%
NHELI 2007-2 Group 1	12.6%	7.0%	18.3%
NHELI 2007-3 Group 1	7.8%	2.5%	13.1%
Aggregate	**11.1%**	**8.5%**	**13.7%**

4. Defendants' Criticisms Of My Average LTV Inflation Rate Extrapolation Are Incorrect As A Matter Of Statistics

77. Dr. Barnett criticizes the method by which I recalculated LTVs in order to extrapolate the results of average inflation rates and, as discussed below, these criticisms also apply to the recalculated LTVs. In addition, Defendants (without support from Dr. Barnett) criticize me for failing to use Defendants' Loan Tapes LTVs (the "Reported LTVs") where the LTVs recalculated using the AVM results (the "Recalculated LTVs") were less than one standard deviation higher than the Reported LTVs. All of these criticisms are incorrect as a matter of statistics.

(a) Dr. Barnett Fails To Acknowledge That My Calculations Take The Use Of A Ratio Into Account, And Has Admitted He Does Not Know How To Calculate LTV

78. Dr. Barnett makes three criticisms of my recalculation of LTV rations using the AVM data. I address each in turn.

79. *First*, Dr. Barnett asserts that, because the AVM value is used in the denominator of the LTV ratio, there is a "systematic upward bias." What Dr. Barnett ignores is that, in addition to recalculating the LTVs, I also calculated the confidence intervals around those recalculated LTVs based on the distribution created by the Monte Carlo simulation. This recalculated distribution – taking into account both Sampling and AVM Variability – is skewed (rather than normal, or bell-shaped, as the AVM distributions are), and the recalculated confidence intervals are asymmetric, because of the effect Dr. Barnett describes. Because the weighted average LTV is calculated using the recalculated confidence intervals from this recalculated distribution, the results take into account exactly the asymmetry Dr. Barnett describes. In other words, the "systematic upward bias" he describes is already reflected in my calculations, not ignored as Dr. Barnett implies.

80. *Second*, Dr. Barnett asserts that the Monte Carlo simulation "compounds" the first issue because, in performing the extrapolations, I selected at random from the 95% confidence interval. Barnett Report ¶ 48. This is specious for the same reason that Dr. Barnett's first criticism is. The confidence intervals I recalculated take this asymmetry into account as well.

81. *Third*, Dr. Barnett criticizes the way I calculated LTV and claims that the method I used to calculate LTV is biased. This is misleading. I followed Dr. Kilpatrick's definition in calculating LTV: I divided the principal amount of the loan by the minimum of the sale price, the appraisal, or the AVM value. As I testified at my deposition, I was also able to confirm that Defendants calculated LTV in a similar fashion on their Loan Tapes, specifically by dividing the principal amount of the loan by the lesser of the sale price or the appraised value. Dr. Barnett admitted at his deposition that he had no expertise in how to calculate LTVs. He also admitted that the effects he describes are inherent in the calculation. He therefore can only point out these

effects; he cannot say whether they are simply the result of the way the LTV is always calculated. That Dr. Barnett finds the method of LTV illogical does not mean that it is the wrong method.

(b) Defendants' Criticisms, Unsupported By Dr. Barnett, Mistake An Input For An Output

82. Dr. Barnett notes that in performing the average inflation calculations, I did not use Dr. Kilpatrick's definition of "inflated" appraisals. That is misleading. Dr. Kilpatrick defined loans where the appraisal was at least one standard deviation above the AVM value as "inflated." Whether an appraisal was "inflated," by this definition, was an individual inquiry as to the difference between the AVM and appraised values. The difference between two values measured in this way can be used to test statistical significance. But I do not understand that to be Dr. Kilpatrick's purpose; instead, he used the difference as a gating threshold to determine which individual appraisals should be subject to further assessment using the Greenfield Credibility Assessment Model (CAM).

83. Defendants (without support from Dr. Barnett, who is silent on this subject) contend that I should have used a cut-off of one standard deviation (also known as measurement at 68% confidence in a normal distribution) employed by Dr. Kilpatrick, solely for the separate purpose of deciding which individual appraisals to analyze for compliance with the applicable appraisal standards. Defendants put forward an alternative version of **Plaintiff's Exhibit 1559**, using the "inflated" cut-off, but in preparing the alternative version Dr. Barnett merely performs the calculation Defendants requested without endorsing it.

84. I used the "inflated" definition where it was statistically appropriate to do so: in extrapolating the percentage of "inflated" appraisals that Dr. Kilpatrick found were not credible using CAM. But I did not use it when calculating average inflation in **Plaintiff's Exhibit 1559**.

This test for "inflation" has no application in the context of extrapolation of *average* inflation, for three reasons. *First*, Defendants confuse an *input* for my extrapolation – the AVM results, with their unique upper and lower confidence bounds at the 68% confidence level – with the *output*, an extrapolated value whose precision is measured at 95% confidence. As explained above, I employed a Monte Carlo simulation to account in my extrapolations for *both* (1) variability in the data created by the use of a sample (rather than an entire population) and (2) variability created by the use of an AVM. Each individual AVM value is an *input* to this calculation. The Monte Carlo simulation allowed me to report a margin of error at the 95% confidence level for these aggregate calculations that took into account both these sources of variability (from sampling and from the AVM) when measuring the precision of the extrapolation, the *output* of my calculations.

85. *Second*, in asserting that I should have discarded any individual AVM value where the difference between the AVM and the reported appraisal value did not pass a test of statistical significance at 68% confidence, Defendants seek to eliminate valid comparative data because they vary individually in magnitude, even though they exhibit, when taken together, both *statistically significant* and in fact *material* effects *at a higher degree of confidence* than 68%. Contrary to Defendants' assertion, the science of statistics specifically enables me to calculate extrapolations that are more precise than the individual inputs per the Central Limit Theorem.

86. The Central Limit Theorem has three key components. If I have a set of random observations where each observation is from a probability distribution, normal (the bell-curve distribution) or not normal, that has a mean of mu and a variance of sigma-squared – these can be any values as long as they are not infinite – then: 1) the expected mean of the set of

observations is also mu (this is the average across all possible samples); 2) the variance of the set of observations is sigma-squared divided by n, and 3) the probability distribution of the average is approximately normal, getting closer to the normal as the sample size n gets larger. What this means is that, as the sample size gets bigger, the estimate of the value in the population (typically the mean) gets more and more precise. Thus, even though I may not have a very precise estimate with one observation, the estimate improves as the sample size increases (point #2), it always points to the real value in the population (point #1), and the final distribution of the mean tends to be bell-shaped even if the original distribution was not.

87. It is possible to measure the statistical significance of the results of a test on an extrapolated value, and doing so here further illustrates Defendants' error. Dr. Kilpatrick has shown that certain individual appraised values reported by Defendants are not one standard deviation or more greater than the related AVM value, even though there are observable differences in the actual data. But because these differences point generally in the same direction, the differences are meaningful and strongly support the conclusion of appraisal inflation. Specifically, when these individual AVM values from the sample are extrapolated to the population, one can test whether the difference between the *average* reported appraised value and the *average* AVM value is greater than one standard deviation. Here, the differences between average Reported LTV and the Average Recalculated LTV in fact are not just one standard deviation or more (*68%* confidence); they are statistically significant – for every single SLG – at the *95%* confidence level.

88. *Third*, to perform the extrapolation as Defendants propose – *i.e.*, to exclude from the extrapolation any inflation, as measured by the AVM, that is not a standard deviation or more

different from the appraisal when measured individually – is fundamentally wrong as a matter of statistics because it ignores relevant data. A simple example illustrates this.

89. Suppose there is a sample of 100 loans, and every loan has an AVM value with an associated standard deviation of +/-15% at the 68% confidence level (one standard deviation for a normal distribution, as here). This would mean that the 68% upper confidence bound on each estimate is the AVM value plus 15%. Finally, suppose that for every loan in the sample, the appraisal value is 14% greater than the AVM value, demonstrating an overwhelming trend of appraisal inflation. According to Defendants' logic, because the observed differences fall within one standard deviation, (1) there is no difference as to the comparative data for each loan, taken individually, (2) all the data points therefore must be excluded, and (3) one must conclude in the aggregate that there is no appraisal inflation at all – even though, both in average and for all loans, the appraisal is 14% greater than the AVM values. Defendants' position is contrary to well-established statistical science, including the Central Limit Theorem mentioned above.

90. *Fourth*, Dr. Kilpatrick's test for whether a loan is "inflated" is based on the comparison of the upper bound generated by the AVM, at 68% confidence, for each individual loan with the related individual appraisal. It has nothing to do with the confidence interval for my extrapolations.

5. Extrapolation Of Percentage of Loans Where Loan Tape LTV Ratio Is Less Than The 95% Lower Bound Of The Simulated LTV Ration

91. The next step in my extrapolations involves the recalculation of the loan-to-value (LTV) ratio for each loan in the AVM Data (672 loans). I relied on the average simulated AVM for each loan and compared each recalculated value with the Loan Tape LTV ratio for each loan. I found that the Loan Tape LTV ratio was less than the 95% Lower Bound of the recalculated LTV ratio based on the simulation results for 40 loans of the 672 loans (or 6.0% of the

population). **Plaintiff's Exhibit 1560**, which I reproduce in Table 38, shows the percentage of loans with such understated LTV ratios for each deal.

Table 38: Percent of Loans where the Loan Tape LTV Ratio Is Less than the 95% Lower Bound of the Simulated LTV Ratio (Count Estimate)

Securitization (SLG)	Percent of Understated Loan Tape LTV Ratios
NAA 2005-AR6 Group 3	5.4%
NHELI 2006-FM1 Group 1	3.2%
NHELI 2006-FM2 Group 1	7.4%
NHELI 2006-HE3 Group 1	10.2%
NHELI 2007-1 Group 2-1	2.2%
NHELI 2007-2 Group 1	8.0%
NHELI 2007-3 Group 1	5.8%
Aggregate	**6.0%**

6. Extrapolation of Distribution of Loans Based on LTV Ranges

92. I also tabulated the count of loans for specific LTV ranges or bounds (LTV lower than 80, LTV greater than or equal to 80, etc.). In addition, I calculated the percentage of loans found in each LTV range and compared it to the percentiles observed in the Population and the AVM Sample. The result of this comparison is presented in **Plaintiff's Exhibit 1561**, which I reproduce in Table 39, **Plaintiff's Exhibit 1562**, which I reproduce in Table 40, and Chart 2.

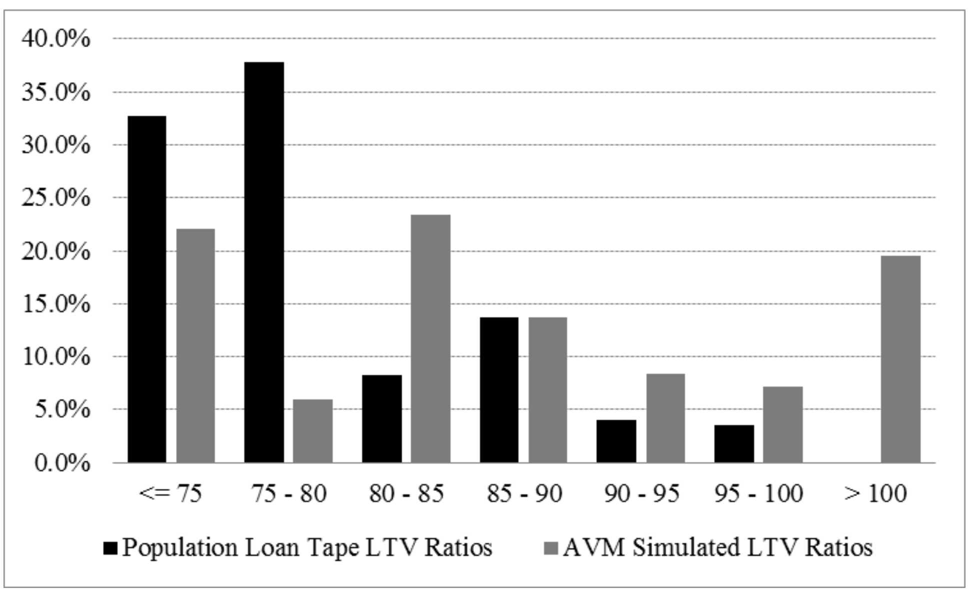
Table 39: Comparison of the Distribution of Loans Based on LTV Ranges (Count Estimate)

LTV Ranges	Population Loan Tape LTV Ratios	AVM Sample Loan Tape LTV Ratios	AVM Simulated LTV Ratios
Less than 75	32.7%	33.8%	22.0%
Between 75 and 80	37.8%	44.8%	6.0%
Between 80 and 85	8.3%	6.0%	23.4%
Between 85 and 90	13.7%	9.2%	13.7%
Between 90 and 95	4.0%	2.5%	8.3%
Between 95 and 100	3.5%	3.7%	7.1%
Greater than 100	0.0%	0.0%	19.5%

Table 40: Comparison of the Distribution of Loans Based on LTV Ranges (Count Estimate)

SLG	LTV ≤ 80%		LTV > 80% to LTV ≤ 100%		LTV > 100%	
	Original	Extrapolated	Original	Extrapolated	Original	Extrapolated
NAA 2005-AR6 Group 3	98.94%	28.68%	1.06%	61.24%	0.00%	10.08%
NHELI 2006-FM1 Group 1	72.16%	30.85%	27.84%	56.38%	0.00%	12.77%
NHELI 2006-FM2 Group 1	80.62%	37.89%	19.38%	42.11%	0.00%	20.00%
NHELI 2006-HE3 Group 1	62.91%	30.68%	37.09%	47.73%	0.00%	21.59%
NHELI 2007-1 Group 2-1	91.77%	21.74%	8.23%	63.04%	0.00%	15.22%
NHELI 2007-2 Group 1	60.78%	27.27%	39.2%	40.91%	0.00%	31.82%
NHELI 2007-3 Group 1	66.8%	17.44%	33.2%	52.33%	0.00%	30.23%
Total	**70.5%**	**28.0%**	**29.5%**	**52.5%**	**0.0%**	**19.5%**

Chart 2: Comparison of the Distribution of Loans Based on LTV Ranges



7. Defendants' Criticisms Of My Extrapolated LTV Ranges Again Mistake An Input For An Output And Are Inconsistent With Their Criticisms Of My Average LTV Inflation Calculations

93. Defendants contend that I should have used the Defendants' Reported LTVs whenever, on an individual level, the difference between the Reported LTV was below the recalculated 95% upper confidence bound for the Recalculated LTV. Defendants provide a calculation, through Dr. Barnett, showing this result; but Dr. Barnett merely performs the calculation asked of him and does not endorse it. Defendants give two reasons why they claim my calculation is wrong: first, that my extrapolation is inconsistent with my decision to use samples sizes of 100 loans to achieve a maximum margin of error of +/- 10% at 95% confidence, and, second, that "[b]y using simulated LTV ratios for all of the sample loans, [Dr. Cowan] produces results that have no statistical significance whatsoever." Defendants are fundamentally mistaken.

94. *First*, Defendants again confuse an *input* for my extrapolation – the AVM results, with their unique upper and lower confidence bounds – with the *output*, an extrapolated value whose precision is measured at 95% confidence. This is wrong, as I have already explained in paragraphs 84-90. *Second*, Defendants' argument about **Plaintiff's Exhibit 1561** conflicts with their argument about **Plaintiff's Exhibit 1559**. In criticizing Table 8, Defendants assert I should have used the 95% confidence upper bound, which is approximately *two* standard deviations, as the cut-off for an "inflated" appraisal. But in criticizing Table 6, they assert I should have used *one* standard deviation as the cut-off. Thus, Defendants say that my LTV extrapolations should exclude individual AVM results (1) based on a confidence level of 95% (approximately two standard deviations), and (2) based on a confidence level of 68% (one standard deviation). This is internally inconsistent and wrong.

8. Further Analysis Of Dr. Kilpatrick's Results

95. It is possible to make a direct comparison between the results from the Monte Carlo simulation and Dr. Kilpatrick's original report for appraisals with values above the 95% upper bound of the AVM because the two results are based on similar data – that is, appraisals that are significantly higher than the AVM results.

96. Based on the results from the simulations, I identified 112 loans with an original appraisal value larger than the 95% upper bound of the AVM estimate. I also find that the number of appraisals exceeding the 95% upper bound from the simulation in each SLG is similar to the number obtained directly from AVM model, indicating that the simulations results are reliable. These results are reflected in **Plaintiff's Exhibit 1563** and are reproduced below.

Table 41: Comparison of Inflated Appraisals (Count Estimate)

Securitization (SLG)	Original Sample Size	AVM Estimate Available	Inflated (from Kilpatrick)	Inflated (from Simulation)
NAA 2005-AR6 Group 3	196	129	19	16
NHELI 2006-FM1 Group 1	100	94	13	11
NHELI 2006-FM2 Group 1	100	95	24	24
NHELI 2006-HE3 Group 1	100	88	19	17
NHELI 2007-1 Group 2-1	100	92	11	10
NHELI 2007-2 Group 1	100	88	18	18
NHELI 2007-3 Group 1	100	86	17	16
Aggregate	**796**	**672**	**121**	**112**

9. Appraisal Standard Estimates

(a) Construction of the Dataset

97. It is my understanding that Dr. Kilpatrick identified 208 loans whose original appraisal values were inflated by at least 15.1% for which AVM results are available. He then assessed the credibility (as that term is used in USPAP) of 199 appraisals using CAM based on

detailed factual inquiry and applicable industry standards and practices at the time. Of the 199 inflated appraisals evaluated, Dr. Kilpatrick concluded that 193 (or 96.98% of those appraisals) could not be considered credible under USPAP and other applicable professional standards applicable to residential appraisal in the 2005 to 2007 period. Applying a more conservative threshold for determining credibility, he concluded that 184 (or 92.46%) of the inflated appraisals were not credible (*i.e.*, breach the appraisal standards). The extrapolation of these results is based on the conservative threshold for determining credibility of appraisals in Dr. Kilpatrick's report – that is, 184 inflated appraisals in the set of 199 inflated appraisals were not credible.

(b) Extrapolation

(i) Methodology

98. I extrapolated the non-credible rate for the subpopulation of loans whose original appraisals were "inflated" (as defined by Dr. Kilpatrick).

99. For extrapolating Dr, Kilpatrick's appraisal results, I chose to use the same method that I used to extrapolate the results of Mr. Hunter's re-underwriting work. I did not extrapolate by FICO stratum because the number of loans reviewed by Dr. Kilpatrick for each SLG is very small. There would be cases where there would not be any loans in a particular FICO stratum.

(ii) Subpopulation of Inflated Loans

A) Aggregate Level Results

100. Approximately 92.18% of the loans with inflated appraisals underlying the SLGs breached the appraisal standards and therefore their original appraisals are not credible. The estimation is made with a 95% confidence level and a margin of error of 4.18%, which means that there is 95% chance that the breach rate of the inflated loan population will fall between

88.0% and 96.4%, and only 2.5% of time the subpopulation breach rate is less than 88.0%. The actual non-credible rate would have been higher had I used the 193 appraisals identified as not credible by Dr. Kilpatrick, instead of the 184 resulting from the application of the more conservative test.

B) SLG Level Results

101. The non-credible rate here is computed as the number of inflated loans for which Dr. Kilpatrick determined that the appraisals were not credible divided by the total number of inflated loans. Dr. Kilpatrick evaluated the same samples of loans evaluated by Mr. Hunter. Accordingly, there is overlap between the loans that contain material underwriting defects and those that were based on inflated and non-credible appraisals. As with the extrapolation of Mr. Hunter's re-underwriting results, the non-credible rate can be computed as the number of the non-credible appraisals in the sample divided by the total number of inflated appraisals in the sample. The results for the SLGs, as well as the 95% confidence intervals and margins of error, are presented in **Plaintiff's Exhibit 1564**, which I reproduce in Table 42.

Table 42: Non-Credible Rates for the SLGs on Loans Determined to Have Inflated Appraisals Only (Count Estimate)

Securitization (SLG)	Non-Credible Rate (conservative)	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	92.59%	76.31%	98.86%	11.28%
NHELI 2006-FM1 Group 1	92.86%	76.58%	99.09%	11.25%
NHELI 2006-FM2 Group 1	89.47%	75.26%	97.02%	10.88%
NHELI 2006-HE3 Group 1	93.10%	77.30%	99.13%	10.92%
NHELI 2007-1 Group 2-1	94.44%	73.10%	99.76%	13.33%
NHELI 2007-2 Group 1	91.18%	76.40%	98.10%	10.85%
NHELI 2007-3 Group 1	96.00%	79.75%	99.87%	10.06%
Aggregate	**92.18%**	**88.01%**	**96.36%**	**4.18%**

102. For the sake of completeness, I also extrapolated the breach rate for all loans underlying the SLGs together using the same method for extrapolation, as explained above. Even under an extremely conservative assumption where the 473 loans in the samples that were not evaluated had credible or reliable appraisals, still approximately 31.35% appraisals in the population of loans would be considered not to be credible. This estimate is provided at a 95% confidence level with a margin of error of 4.16%, which means that there is 95% probability that the breach rate is between 27.19% and 35.51%, and there is only 2.50% chance that the population breach rate is less than 27.19%. These results are reflected in **Plaintiff's Exhibit 1565**, reproduced below.

Table 43: Non-Credible Rates for the SLGs (Entire Population)

Securitization (SLG)	Non-Credible Rate	95% Lower Bound	95% Upper Bound	Margin of Error
NAA 2005-AR6 Group 3	19.4%	14.2%	25.8%	5.8%
NHELI 2006-FM1 Group 1	27.7%	19.1%	37.7%	9.3%
NHELI 2006-FM2 Group 1	35.8%	26.3%	46.2%	9.9%
NHELI 2006-HE3 Group 1	30.7%	21.4%	41.3%	9.9%
NHELI 2007-1 Group 2-1	18.5%	11.9%	27.0%	7.5%
NHELI 2007-2 Group 1	35.2%	25.5%	46.0%	10.2%
NHELI 2007-3 Group 1	27.9%	19.0%	38.4%	9.7%
Aggregate	**31.3%**	**27.2%**	**35.5%**	**4.2%**

103. After extrapolating the appraisal standard results of the samples to the populations, I can conclude that most of the inflated loans in the seven SLGs have original appraisal values that are not credible.

104. For the extrapolated non-credible population, I also prepared a cross tabulation of the LTV as represented on the loan tapes and as simulated. **Plaintiff's Exhibit 1566**, which I

reproduced in Table 44, shows that a majority of these non-credible inflated appraisals on an extrapolated basis also had LTV ratios above 100 percent.

Table 44: Mapping of Original LTV to Extrapolated (Simulated) LTV for Non-Credible Appraisals: 10(a) for Extrapolated Count and 10(b) for Extrapolated Percentages (Count Estimate)

		Overall							
		Recalculated AVM LTV (Count)							
		0-75	**75-80**	**80-85**	**85-90**	**90-95**	**95-100**	**100+**	**Total**
Original LTV	**0-75**	30	3	3	14	5	2	11	68
	75-80	0	0	0	2	15	20	36	73
	80-85	0	0	0	0	0	2	8	10
	85-90	0	0	0	0	0	0	19	19
	90-95	0	0	0	0	0	0	4	4
	95-100	0	0	0	0	0	0	10	10
	100+	0	0	0	0	0	0	0	0
	Total	**30**	**3**	**3**	**16**	**20**	**24**	**88**	**184**

		Overall						
		Recalculated AVM LTV (Percent)						
		0-75	**75-80**	**80-85**	**85-90**	**90-95**	**95-100**	**100+**
Original LTV	**0-75**	44.1%	4.4%	4.4%	20.6%	7.4%	2.9%	16.2%
	75-80	0.0%	0.0%	0.0%	2.7%	20.5%	27.4%	49.3%
	80-85	0.0%	0.0%	0.0%	0.0%	0.0%	20.0%	80.0%
	85-90	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	90-95	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	95-100	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	100+	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

105. I provide a different representation of the same data in **Plaintiff's Exhibits 1567-1568 and 1678-1679**, reproduced below, showing the impact of non-credible loans on the originally reported distribution of LTV.

Table 45: Comparison of Original LTV to Extrapolated (Simulated) LTV Due to Non-Credible Appraisals Only (Count Estimate) **Plaintiff's Exhibit 1567**

SLG	LTV ≤ 80%		LTV > 80% to LTV ≤ 100%		LTV > 100%	
	Original	Extrapolated	Original	Extrapolated	Original	Extrapolated
NAA 2005-AR6 (3)	100.0%	82.2%	0.0%	8.5%	0.0%	9.3%
NHELI 2006-FM1 (1)	79.8%	61.7%	20.2%	28.7%	0.0%	9.6%
NHELI 2006-FM2 (1)	80.0%	62.1%	20.0%	25.3%	0.0%	12.6%
NHELI 2006-HE3 (1)	62.5%	46.6%	37.5%	36.4%	0.0%	17.0%
NHELI 2007-1 (2)	89.1%	73.9%	10.9%	16.3%	0.0%	9.8%
NHELI 2007-2 (1)	61.4%	50.0%	38.6%	29.5%	0.0%	20.5%
NHELI 2007-3 (1)	66.3%	51.2%	33.7%	33.7%	0.0%	15.1%
Total	**78.6%**	**62.5%**	**21.4%**	**24.4%**	**0.0%**	**13.1%**

Table 46: Extrapolated Fraction of Non-Credible, Inflated Appraisals (Count Estimate) **Plaintiff's Exhibit 1568**

Securitization & SLG	Average Non-Credible of Nomura Appraisals	95% Lower Bound Non-Credible of Nomura Appraisals	95% Upper Bound Non-Credible of Nomura Appraisals
NAA 2005-AR6 (3)	92.6%	76.3%	98.9%
NHELI 2006-FM1 (1)	92.9%	76.6%	99.1%
NHELI 2006-FM2 (1)	89.5%	75.3%	97.0%
NHELI 2006-HE3 (1)	93.1%	77.3%	99.1%
NHELI 2007-1 (2-1)	94.4%	73.1%	99.8%
NHELI 2007-2 (1)	91.2%	76.4%	98.1%
NHELI 2007-3 (1)	96.0%	79.8%	99.9%
Total	**92.2%**	**88.0%**	**96.4%**

Table 47: Extrapolated Increases of LTV for Non-Credible, Inflated Appraisals for Nomura Loans (Count Estimate) **Plaintiff's Exhibit 1678**

Original LTV	Recalculated AVM LTV (Percent) 0-75	75-80	80-85	85-90	90-95	95-100	100+
0-75	44.1%	4.4%	4.4%	20.6%	7.4%	2.9%	16.2%
75-80	0.0%	0.0%	0.0%	2.7%	20.5%	27.4%	49.3%
80-85	0.0%	0.0%	0.0%	0.0%	0.0%	20.0%	80.0%
85-90	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
90-95	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

95-100	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
100+	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Total	**16.3%**	**1.6%**	**1.6%**	**8.7%**	**10.9%**	**13.0%**	**47.8%**

Table 48: Comparison of Extrapolated LTV to Original Reported LTV Due to Non-Credible Appraisals (Count Estimate) **Plaintiff's Exhibit 1679**

SLG	LTV ≤ 80%		LTV > 80% to LTV ≤ 100%		LTV > 100%	
	Original	**Extrapolated**	**Original**	**Extrapolated**	**Original**	**Extrapolated**
NAA 2005-AR6 (3)	100.0%	82.2%	0.0%	8.5%	0.0%	9.3%
NHELI 2006-FM1 (1)	79.8%	61.7%	20.2%	28.7%	0.0%	9.6%
NHELI 2006-FM2 (1)	80.0%	62.1%	20.0%	25.3%	0.0%	12.6%
NHELI 2006-HE3 (1)	62.5%	46.6%	37.5%	36.4%	0.0%	17.0%
NHELI 2007-1 (2)	89.1%	73.9%	10.9%	16.3%	0.0%	9.8%
NHELI 2007-2 (1)	61.4%	50.0%	38.6%	29.5%	0.0%	20.5%
NHELI 2007-3 (1)	66.3%	51.2%	33.7%	33.7%	0.0%	15.1%
Total	**78.6%**	**62.5%**	**21.4%**	**24.4%**	**0.0%**	**13.1%**

10. Dr. Barnett's Criticisms Of Table 9 Are Incorrect As A Matter Of Statistics

106. Dr. Barnett does not take issue with how I extrapolated the results reflected in Table 9, but makes various arguments in support of an assertion that many of the results could be the product of chance alone. He is wrong. Dr. Barnett initially asserts that one would expect 16% of the loan tape valuations would be "inflated" (using Dr. Kilpatrick's definition of at least one standard deviation greater than the AVM value) by chance if the loan tape valuations were correct and the AVM were reliable. At his deposition, however, Dr. Barnett admitted that, because the percentage of loan tape valuations that were "inflated" exceeded 16% (and was in

fact 31%), the hypothesis that the loan tape valuations were correct and the AVM was reliable, was false. One or both of those assumptions must be wrong.

107. Dr. Barnett then fell back on an alternative calculation by which, he asserted, the number of false positives "might be approximated as 90." This is similarly wrong for several reasons.

108. *First*, there is the fundamental problem of defining a "false positive" in this context. A false positive is an indication by a test that a certain factor is present when, in fact, that factor is not present. An example is a test for a disease that sometimes indicates that the patient has the disease when in fact the patient does not. But that principle has no application in this context, because the AVM and CAM do not measure the same thing. The AVM measures the value of the property, and the CAM assesses the validity of the underlying appraisal under USPAP. Thus, the AVM does not act as a test on the CAM, and the CAM does not act as a test on the AVM. It is therefore entirely possible that all of the appraisals are not credible under USPAP and all of them are inflated.

109. *Second*, the number of times that the combination of an appraisal that is a standard deviation or more greater than the AVM value and a finding using CAM that the appraisal is not credible occurs is essentially unknowable; that is why one must use a probabilistic assessment. It is also an arbitrary inquiry, given that Dr. Kilpatrick used the one-standard-deviation cut-off purely as a way to decide which appraisals to assess using CAM, and specifically states that he does not believe that appraisals below that cut-off are necessarily credible under USPAP.

110. *Third*, Dr. Barnett admitted in his deposition that his equation (which he appears to have created himself, as he cites nothing in support of its use here) assumes that the number of

false negatives (*i.e.*, a failure to detect an "inflated" appraisal that is not credible using CAM) is zero. This is an unsupported – and unsupportable – assumption, and, as Dr. Barnett was further constrained to admit, if the number of false negatives goes up, the number of false positives goes down. It is also yet another indication that Dr. Barnett's calculation in reality merely assumes that there are "false positives" in order to demonstrate that there are "false positives." In other words, Dr. Barnett assumes what he is trying to prove.

C. The Results of My Extrapolations Are Sufficiently Precise

111. I selected my initial sample sizes to achieve a maximum margin of error of +/- 10% at the 95% confidence level for binary questions. (It is not possible to know *ex ante* what margin of error at a particular confidence level will be achieved for continuous variables such as LTV; but, generally speaking, the larger the sample size, the small the margin of error at a particular confidence level.) Despite the unavailability of some loan files, I was largely able to achieve my target, and my results are sufficiently precise to make reliable estimates about each SLG and the SLGs in the aggregate.

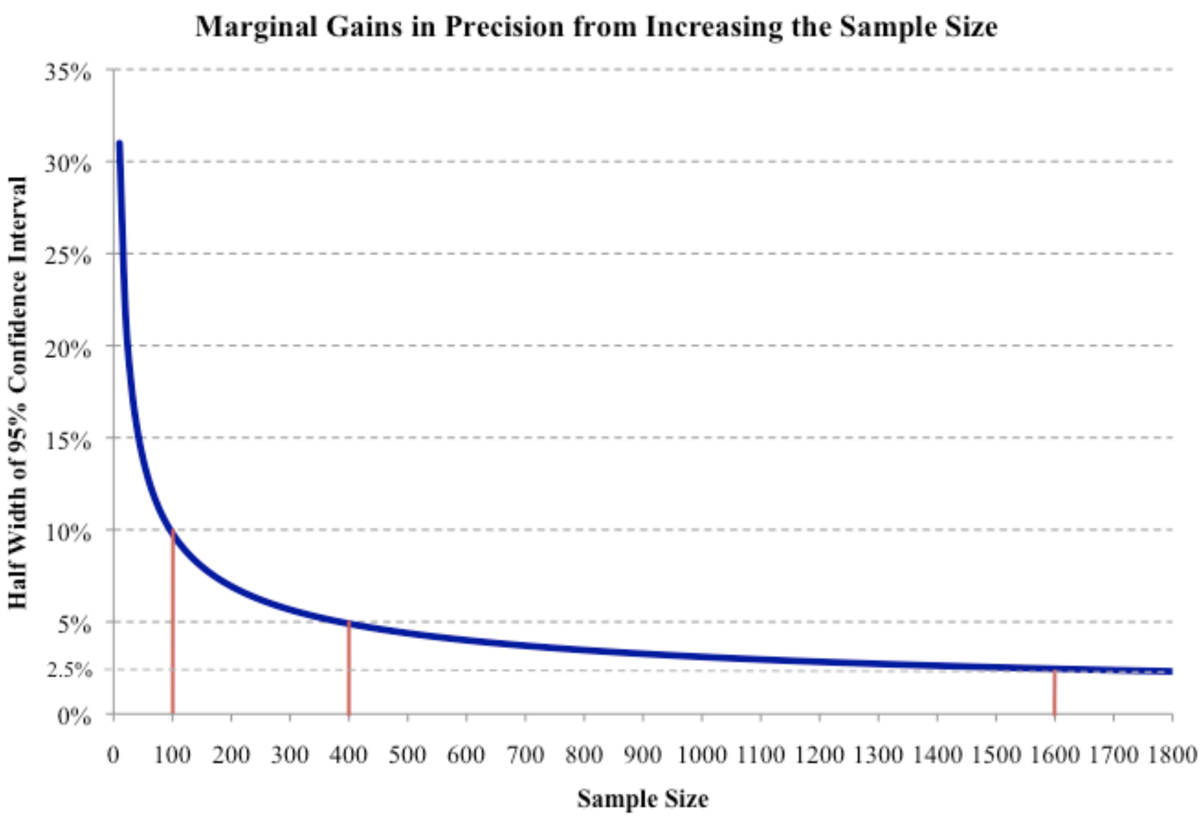
1. A 95% Confidence Level, With a Maximum Margin of Error of +/- 10%, Strikes the Correct Balance Between Cost and Accuracy

112. A 95% confidence level with a maximum margin of error of +/- 10% is scientifically valid. The confidence level of 95% is standard and well supported in statistics. Traditionally, scientists adopt the 95% level of confidence. Dr. Barnett agrees.

113. A target of a 10% margin of error, with a 95% confidence level, strikes the correct balance between cost and accuracy for two primary reasons. The first reason that increasing sample size would generate only marginal benefits—without commensurate benefits in increased precision—is that the gain in reliability due to a larger sample size increases only as the square root of the sample size. This is demonstrated as Chart 3 below. As the sample size increases

from 1 to 100, there is a large increase in reliability (meaning smaller confidence intervals for 95% confidence). As the sample size increases from 100 to 400, however, the increase in precision, and associated reduction in confidence interval, is halved for a quadrupling of the sample size. To halve the margin of error again, from plus or minus five percent to plus or minus 2.5%, the sample size has to quadruple again, from 400 to 1,600.

Chart 3: Diminishing Returns for Increasing Sample Sizes



114. As shown in this chart, decreasing the margin of error below +/- 10% by increasing the sample size imposes large costs without commensurate benefits in increased precision.

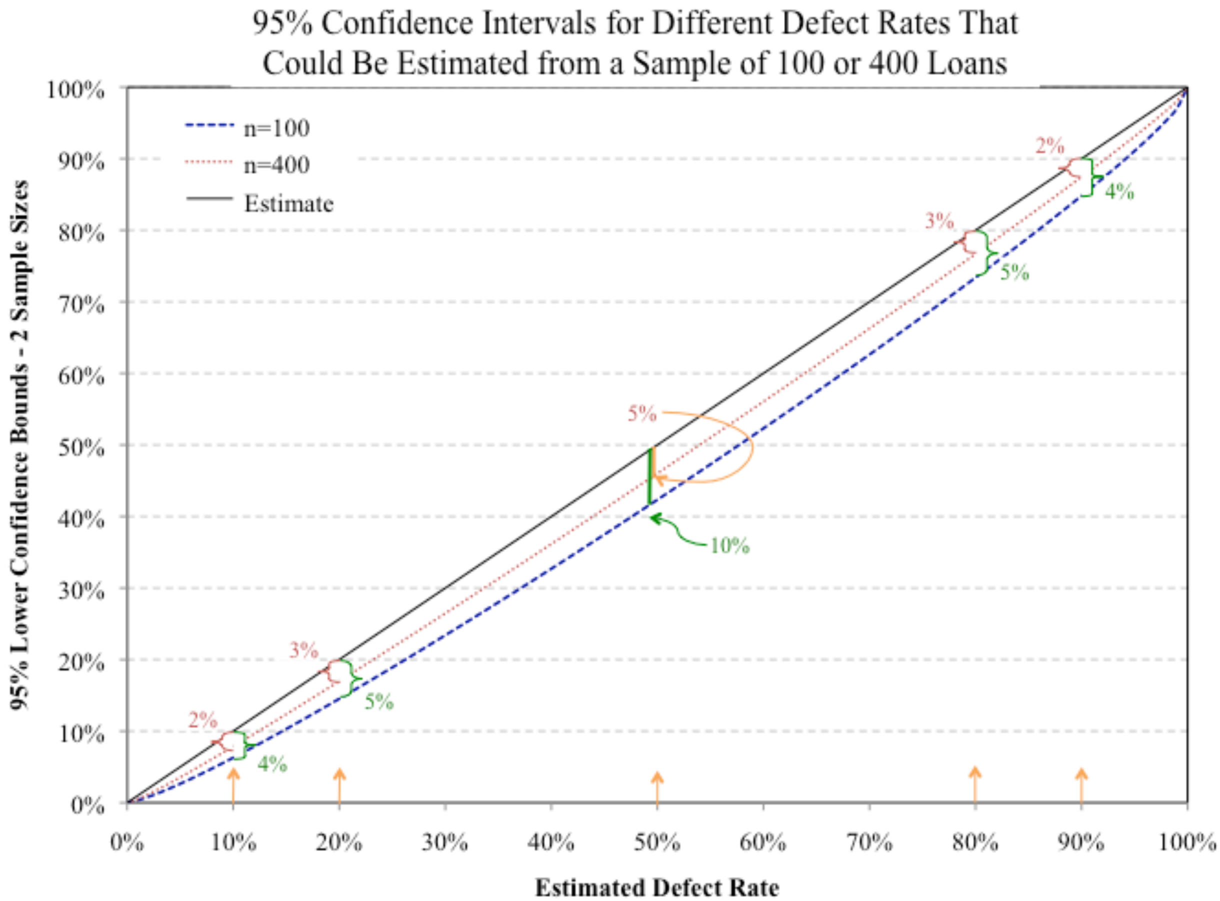
115. The second reason that increasing sample size would generate only marginal benefits is that the +/- 10% is merely the maximum margin of error for this confidence level, and it occurs only when the percentage of Defective Loans is 50%. Fifty percent is the scenario

where variability is at its greatest: half Defective Loans and half not. When the variability decreases—that is, when the percentage deviates from 50% in either direction—the margin of error—and thus confidence interval—becomes smaller. As the intervals shrink, the marginal benefit of a larger sample size shrinks as well.

116. As the estimated defect rate deviates from 50% in either direction, the difference in confidence interval for samples of 100 and 400 decreases. This is shown in Chart 4 below, where the 95% lower bound confidence level for sample sizes of 100 and 400, corresponding to maximum margins of error of +/- 10% and +/- 5%, respectively, is shown for all possible percentages of Defective Loans, from zero to 100%. As **Chart 4** demonstrates, quadrupling the sample size, from 100 to 400, does not yield a commensurate reduction in the 95% range across all possible percentages of Defective Loans. At 50%, or maximum variability, the range is +/- 10% for a sample size of 100 and +/- 5% for a sample size of 400. When the estimated rate is 20%, the 95% range for a sample size of 100 is +/- 5%, whereas for a sample size of 400 the 95% range is +/- 2.5%. When the estimated defect rate is 10%, the 95% range for a sample size of 100 is +/- 4%, while for a sample size of 400 it is +/-2%. As the defect rate approaches zero, the 95% range must also approach zero, regardless of sample size. The same phenomenon occurs for the corresponding values above 50%, as shown in **Chart 4**.

117. Finally, in the small number of instances where the margin of error at 95% confidence was larger than 10%, the extrapolated values were so high that even taking the lower bound would yield a very high number.

Chart 4: 95% Lower Bound For Samples Of Size 100 And 400 For All Defect Rates



IV. Extrapolation Of RBS's Diligence Sample Results

118. I also extrapolated the results from RBS's diligence samples (performed in its capacity as an underwriter) for the NHELI 2007-1 and NHELI 2007-2 Securitizations. For these transactions, RBS sampled from the Securitization, not from the SLGs. For the NHELI 2007-1 Securitization, RBS drew two samples but none specifically from Group II-1, the SLG at issue. For NHELI 2007-2, RBS drew one sample from the entire securitization but not from Group I, the SLG at issue.

119. A portion of each of these samples was, according to RBS's description, "semi-random." By this, RBS appears to have meant that the sample was stratified by loan size and "skew[ed]" in favor of higher balance loans, but was otherwise random. Clayton reviewed these samples and provided grades.

120. Although RBS performed no extrapolation, I have attempted to extrapolate the diligence results to the population from which the diligence samples were selected (not to the SLGs because, as noted, RBS did not sample from the SLGs). To extrapolate the results, I make the following assumptions: (1) although it is not possible to truly extrapolate RBS's "semi random" samples with the limited information provided by Defendants' expert Charles H. Grice, I assume that the "semi random" sample is a true random sample for present purposes and (2) the defect rate shall be defined by the number of loans graded EV2W and EV3 by Clayton for either credit or compliance review and that were selected on a "semi random" basis. With the defect rates, I calculated the exact binomial confidence interval and the margin of error of the RBS samples.

121. **Plaintiff's Exhibit 1680** (reproduced below) shows the results of my statistical analysis for the "semi-random" samples.

Table 49: Statistical Analysis Of Semi-Random RBS Diligence Samples (Count Estimate)

Samples	Population Size - Non Adverse	Actual Sample Size	Semi Random Sample Size	EV2W & EV3 Loans In Semi Random Sample	Defect Rate	95% Lower Bound	95% Upper Bound	Margin Of Error
NHELI 2007-1 (Group 2)	1576	102	32	9	28.1%	13.9%	46.6%	16.3%
NHELI 2007-2	5076	306	138	39	28.3%	21.0%	36.4%	7.7%

122. For the sample selected from Group 2 of the NHELI 2007-1 Securitization, the defect rate is 28.1%. The margin of error is +/-16.3%. In other words, with 95% confidence, the number of defective loans in Group 2 can be expected to range from 13.9% to 46.6%. For the sample in the NHELI 2007-2 Securitization, the defect rate is 28.3%. The margin of error is +/-7.7%. In other words, with 95% confidence, the number of defective loans in the securitization can be expected to range from 21.0% to 36.4%.

Pursuant to 28 U.S.C. § 1746, I declare under penalty of perjury that the foregoing is a true and correct statement of my opinions in this Action.

CHARLES D. COWAN, Ph.D.

Executed on this 7th day of March, 2015 in San Antonio, Texas.